Credit growth in China: determinants and consequences

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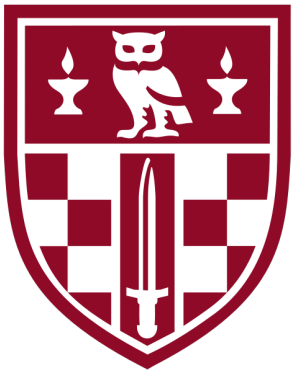

Xiaohong Chen

Department of Economics, Mathematics and Statistics
Birkbeck, University of London

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I would like to dedicate this thesis to my loving parents,
and my greatest supervisors,
Professor Edward John Driffill and Professor Ronald Patrick Smith.

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Declaration

I hereby declare that this thesis is the result of my own work. The thesis has not been submitted, in whole or in part, for consideration for any other degree or qualification at this university or any other institute of learning and complies with Birkbeck, University of London guidelines on length and format.

Xiaohong Chen
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Abstract

Since 1978, China saw rapid growth of both output and credit as it evolved from a centrally-planned, closed economy to a market-based open economy. This thesis provides an empirical analysis of the role of credit and money in China, within a standard theoretical framework, and examines the relative roles of state and market in their growth. This empirical analysis can contribute to the development of theoretical analysis and policy proposals but they are beyond the scope of this thesis. Chapter 1 introduces the thesis. Chapter 2 identifies credit cycles and show that Chinese credit booms clustered in between 1984-88, 1992-94, and 2009-11, around big political conferences. We also examine the role of monetary policies. This analysis suggests that Chinese credit cycles are partly state-driven. Chapter 3 conducts a heterogeneous panel analysis of loan growth for a panel of 14 Chinese listed banks, with data for 2008Q1-2018Q4. Loans are the major form of credit. These 14 banks represent a large share of total bank assets and we group them into various bank-clusters. The results suggest that, whilst there remains a large degree of state influence on Chinese banks, there is evidence for market exposure even at a time of unprecedented state interventions following the global financial crisis. Chapter 4 investigates money demand since credit expansion in China has been accompanied by monetary expansion. An unrestricted VAR suggests a regime shift in 1992 when Deng's reforms deepened. A cointegrating VECM is estimated over 1980Q1-1992Q4 and (1993Q1-2018Q3). We find two cointegrating vectors determining money and income, showing an IS/LM relationship. The results provide evidence on China's economic transition to a market-based system, based on stable money and goods market equilibria. The short-run adjustment equations can be given interpretations in terms of a Phillips Curve and a Taylor Rule. Chapter 5 concludes.

Table of contents

List of figures

List of tables

Chapter 1

Introduction

1.1 Motivation

The rapid development of the Chinese economy over the last four decades is unprecedented. No large country has grown so fast for so long. China adopted a set of economic and financial market reforms that led to gradual transformation from a state-driven planned economy to a decentralised market-economy (socialist market economy). In the process there was a rapid financial development in which credit growth played a central role. The credit-to-GDP ratio increased from 39.49% in 1978, exceeded 100% in 1993 for the first time, and kept rising to above 200% in 2016 (Figure 1.1). Credit growth remains a central issue. In late 2019 there was concern about the role of credit in the slowing Chinese growth rate. Despite its importance for both the economy and policy, few studies systematically address the many levels of the role of credit in China. Since there remain many unanswered questions about Chinese credit growth this thesis intends to provide a systematic review of the topic and try to answer some of the important questions about it.

We approach the role of credit for Chinese financial development and economy from three angles: the role of politics in credit cycles, the determinants of Chinese bank-lending, and the interactions with the wider economy.

What is the role of politics in Chinese credit cycles? We answer this question first through examining the features of Chinese credit cycles and discussing measurement and identification issues. We then discuss the relationship between key financial and macroeconomic variables and credit growth in China since 1978 and investigate the role of Chinese monetary policy and the link between Chinese political conferences and the credit cycle. We find that credit booms happen around the important conference dates, indicating an important political component.

What determines Chinese bank loan growth? We investigate the role of bureaucratic and economic factors in determining loan growth in Chinese banking. We employ a novel bank-level panel dataset capturing lending characteristics for 14 listed Chinese banks from 2008-18, and distinguish the deterministic elements which represent the bureaucratic planned factors from the economic factors. The bureaucratic variables are very important, explaining a large part of the variation in loan growth while the economic factors are significant for the seven joint equity commercial banks when they are pooled as a group. This provides some evidence for market exposure for the joint equity commercial banks.

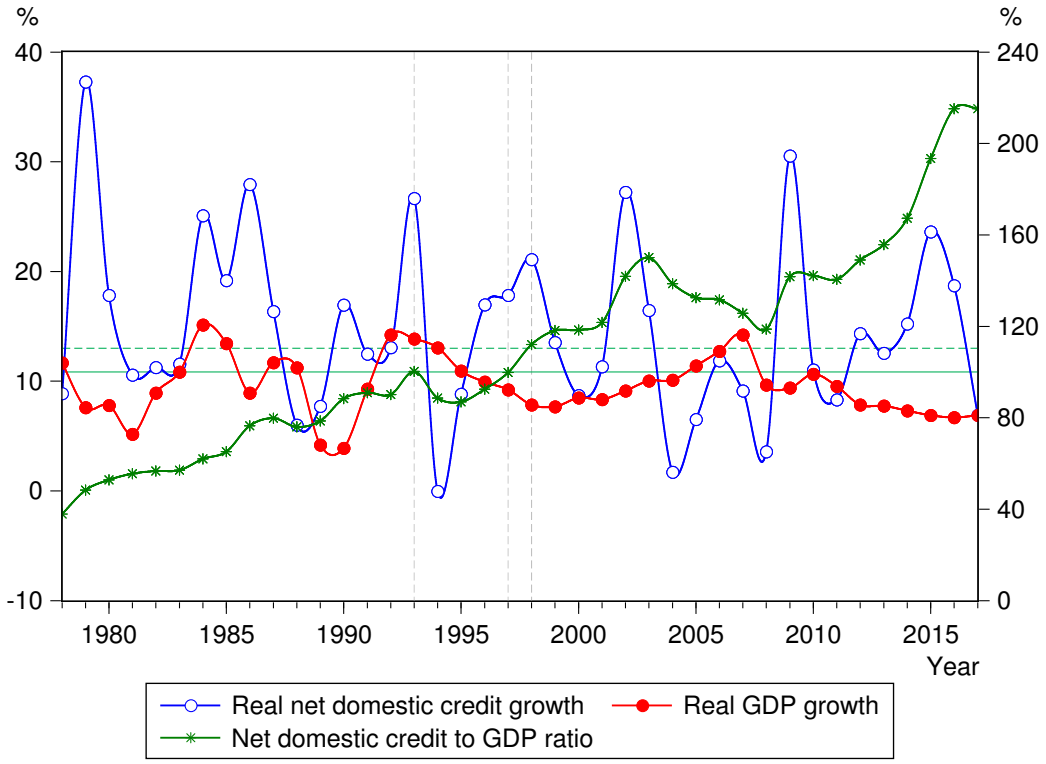
How does money interact with Chinese macroeconomic variables? Money and credit move very closely together in China and in this chapter we use money because of its close relationship with credit. We consider the interactions between money, income, inflation, interest rates and exports. In particular, we ask to what extent the interactions can be described in terms of the traditional IS-LM model of a market economy and to what extent there is evidence on the nature of China's transformation to a market economy as well as on the degree to which Chinese money and credit growth is linked to development of the real economy. We first use a non theoretical unrestricted vector autoregression, VAR, to describe the linkages in terms of patterns of Granger causality. To allow us to identify the theoretical long-run equilibrium IS and LM relationships we then use a restricted cointegrating vector error correction model and succeed in identifying the structural IS and LM curves, something which has not been done before. This has important implications for monetary policy.

In the remainder of this introduction, we provide a general context about the role of state, market and credit in China, then, given that our focus is on credit and financial markets, we provide an overview of Chinese financial market reforms. Finally we have a short outline of the thesis.

1.2 State, market, and credit in China

Any research about China must take account of the differences between China and the rest of the world in aspects such as institutional structure, economic development, and financial systems. While since 1979 there has been a transformation involving liberalisation and opening of the Chinese economy, the public sector retains a large degree of powers of intervention, which comes in various, often subtle, degrees. Investment, lending and interest rate policies are excessively skewed towards state-owned enterprises (SOEs) and designated priority sectors (Zhou et al., 2015). Privatized SOEs continue to benefit from government support such as low interest rates and government subsidies relative to private enterprises, but both SOEs and privatized SOEs significantly under-perform in profitability compared

Fig. 1.1 Credit and economic growth in China.



Note: The left axis is for the real net domestic credit growth, GDP growth. The right axis is for the net domestic credit to GDP ratio. The green dashed line represents the average ratio of net domestic credit to GDP, 110.34%. The green solid line represents 100% horizontal level for the right axis.

to private firms (Harrison et al., 2019). However, Lin and Bo (2012) show that during 1999-2008, state-ownership does not necessarily help reducing firm's financial constraints on investment. Against this backdrop we take stock of China's economic transformation and evaluate its financial development following the introduction of the policy of reformation and opening of the Deng Xiaoping administration 1978.

Credit in China plays a crucial role in this. It is an important link in monetary transmission. It finances production, consumption, and capital formation, which in turn affects economic activity. But Cecchetti and Kharroubi (2018) stated that,

> "Finance and growth are intimately connected. [...] finance could very well be a two-edged sword. When credit is relatively low, or the financial sector's share of employment modest, it adds to growth. But there is a threshold beyond which it becomes a drag. There is now considerable evidence that productivity grows

> more slowly, when a country's government, corporate or household debt exceed 100 percent of GDP".

As noted above since 1978, the credit growth in China has far outpaced GDP growth. The credit ratio (credit-to-GDP) had an increasing trend, reached 39.49% in 1978, exceeded 100% in 1993 for the first time, and kept rising to above 200% in 2016. Average real GDP growth was 9.87% from 1978 to 1993. Since 1993, though China's credit has exceeded 100% of GDP, the threshold suggested by Cecchetti and Kharroubi (2018), China's GDP growth was just slightly lower (9.41%) and much less volatile thereafter. The slower income growth, such as the gradual economy decrease between 2010 and 2016, was likely influenced by the financial crisis rather a high credit ratio. In a nutshell, descriptive evidence on Chinese credit and income growth does not seem to fully support the idea of Cecchetti and Kharroubi (2018). This might indicates some different characteristics of China's credit with respect to the credit cycles, booms, and determinants. For example, the influence of the state on credit such as loan quota and window guidance might contribute to the increasing credit ratio but stable and high economic growth.

But the IMF deputy managing director, Furusawa, in 2017, claimed that Chinese growth relying on credit expansion has problems and might be fundamentally unsustainable. The near-term outlook of the Asia economy is clouded with significant uncertainties and risks, and a key uncertainty is that China's growth remains reliant on rapid credit growth that could cause problems down the road, even though China's rebalancing process continues (Furusawa, 2017). In the same year, a comment from Variant Perception, a leading independent investment research provider, highlights this:

> "The macro-economic landscape has profoundly changed since the financial crisis. Developed markets deleveraged, and emerging markets became the engine of global credit and money growth. [...] As always, China is a pivotal player. [...] While this growth in EM (emerging market) credit was welcome in the aftermath of the crisis, it is arguably now a destabilizing force for the global economy. Half of the countries with the 15 highest Variant Perception Debt Crisis Scores are EMs, the top one being China."[1]

In such a narrative China might even be perceived as a threat to the global economy: "When in doubt over the past 10 years, it has made sense to blame China" (Authers, 2018).

Given the fact that China has different institutional system and is transforming to a socialist market economy, the crucial role of credit playing in China's reform process, the fact

[1] EM and China Driving Global Credit Growth, https://www.variantperception.com/2017/08/05/em-china-driving-global-credit-growth/.

that China has a credit ratio exceeding 100% but still keeps high economy growth, and the potential credit risks, this thesis takes three angles to evaluate Chinese credit markets: credit cycles, determinants of Chinese bank-lending, and interactions with the wider economy.

Credit markets depend on several other factors, such as an economy's institutional structure. China is a socialist market economy, which makes its monetary policies and financial development different from most other countries. For example, institutional influences may prevent development of systemic financial risks even though China has a rapid credit growth. Market forces also affect credit markets. Chinese financial market reforms had important implications for credit markets. Therefore, we argue that credit growth in China is increasingly driven by market forces. With a population of 1.3 billion, China has surpassed Japan to become the world's second largest economy based on the nominal GDP level from 2010. Yet China remains a developing country (its per capita income is still a fraction of that in advanced countries) and its market reforms are incomplete. This point also makes China different from other countries. Hence, credit changes in China may have their own characteristics. To provide more detail on these characteristics we next give a short history of Chinese financial reforms.[2]

1.3 Overview of Chinese financial market reforms

1.3.1 Central bank and monetary financial institutions.

Since China's reform and openning-up policy, a large number of banks and banking regulatory institutions were established, which broke the situation that the People's Bank of China (PBoC) was the sole bak in China bearing high monopolistic power.

Before 1978, the People's Bank of China was not a central bank in the traditional sense, but acted as China's sole lender (EI-Shagi and Zheng, 2018). The PBoC not only managed the macroeconomy, but supplied commercial financial services. In the late 1970s and early 1980s, China established four specialized banks (Bank of China (BOC), China Construction Bank (CCB), Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC)) which separate central banking from commercial banking. From 1984, China formed a dual banking system including PBoC and specialized banks. Specialized banks focused on their own industry with no competition within markets and were completely

[2]For overview of Chinese financial reforms, we referred online information, documents, and speeches such as speech by Mr Yi Gang, Governor of the People's Bank of China, to commemorate the 40th anniversary of China's economic reform and the 70th anniversary of the People's Bank of China, Beijing, 17 December 2018, https://www.bis.org/review/r181220h.htm.

government owned.[3] From 1994, the four specialized banks were reformed to the big four wholly state-owned commercial banks. Further shareholding reforms were approved by the State Council in September 2003. Accordingly, the big four banks (BOC, CCB, ICBC, ABC), alongside Bank of Communications, underwent substantial structural reforms to their corporate governance and shareholder base that resulted in public listing of these banks. Since 2011, BOC, ICBC, ABC and CCB were successively included in the list of global systemically important banks (G-SIBs).

To adapt to the demand of the socialist market economy, from 1980s, China also established joint-equity commercial banks to break the monopoly of specialised banks and form a multi-level and multi-type financial system. In 1995, the State Council decided to establish city cooperative banks, having urban enterprises, residents, and local investors as shareholders. There were 121 city commercial banks operating in Jun 2003 and 134 in 2018. Such banks enhance competitiveness in the financial market.

From 1984, the PBoC supervised the banking, securities, insurance and trust industries, with particular focus on planning and administrative supervision. Bank supervision during this period was mainly conducted around market access, with emphasis on approving new privately owned financial institutions. In 1993, the State Council clarified that the function of the PBoC is to form and implement monetary policy and financial regulation. From 1994, the PBoC therefore started to implement complete market-based financial supervision, auditing business activities of various financial institutions and gradually establishing specific regulatory systems, among other measures. In 2003, China established the China Banking Regulatory Commission to perform functions of the main banking regulator, formerly exercised by the PBoC. In 2018, China integrated the China Banking Regulatory Commission (CBRC) and the China Insurance Regulatory Commission to form the China Banking and Insurance Regulatory Commission (CBIRC). The CBRC's responsibility of drafting important laws and regulations for the banking and insurance industry is assigned to the PBoC.

1.3.2 Capital market reform

There was no financial market in China before 1978. From 1979 onwards, indirect financing market was developed, in which banks were established as main intermediary institution. In the meantime, the direct financing market developed, which was divided into money and

[3]The transformation of China's banking system is described in (EI-Shagi and Zheng, 2018) as follows: "First attempts for further reform towards a market oriented financial system were made in the late 1980s and early 1990s, but the major reforms were introduced in 1994. In 1992, the 14th National Congress of the CPC decided to introduce a new banking system, comprised of three policy banks - responsible for distributing government funds-, and four commercial banks - which eventually evolved into the modern ear big four. Still, those banks were highly specialized, and are (until today) fully state owned."

capital market. From 1985, a growing number of enterprises began to raise funds by issuing bonds and stocks and banks began to issue bonds. A financial market gradually emerged in China. China established Shanghai Stock Exchange in Nov 26, 1990 and Shenzhen Stock Exchange in July 3, 1991. In 1992, China established China Securities Commission and China Securities Regulatory Commission. The China Securities Commission mainly managed the national stock market until 1998 when the China Securities Commission was closed. From 1999, the China Securities Regulatory Commission regulated the stock market. In 2003, the China Banking Regulatory Commission initiated the shareholding reform and listing of the big four commercial banks. There has been 14 listed Chinese banks including 3 of the big four (Agricultural Bank of China listed in 2010) by the end of 2008 and 46 at the end of 2018.

1.3.3 Credit market reform

From 1950s to the late 1970s, China's management system of credit funds was a "unified deposit and loan" system. That is Branches of the PBoC absorbed deposits and made loans according to the planned target of the Head Office. Branches of the PBoC had to report to the head office. Then China's management system of credit funds reformed in several stages.

From 1979 to 1984, it transferred to a system of "unified plan, hierarchical management, linking savings and loans, responsibility of the credit balance". "unified plan" meant all banks had to prepare credit balance plans in accordance with the uniform provisions of the PBoC head office. Plans received from local branches were then collected by the head office, to prepare a national plan. Based on this national plan the PBoC then assigned plans to local branches in a top-down manner. "hierarchical management" means under the national unified plan, the responsibility and authority of each bank branch to manage credit funds is clarified within the scope of its credit balance. "linking savings and loans" means for banks that adopt the credit balance package, the absorption of deposits and the issuance of loans are linked within the scope of the package project. When deposits exceed loans, the resulting surplus was transferred to the Head Office. Equally local branches that reported deficits were compensated by the Head Office. "responsibility of the credit balance" refers to cases, where the approved credit balance is to be used on a lump sum basis. Then the balance of deposits must be completed, and the balance of loans must not be exceeded. Under the lump sum plan, if the deposit plan cannot be completed and the loan cannot be recovered on schedule, less loans will be issued. This system allows for flexible application of centrally planned management of credit funding. It gives a hybrid-state between central and decentral credit supply, that shows first attempts at transforming China's credit supply into a decentralised system.

From 1985 to 1993, the credit fund management system evolved into a system of "the PBoC making and approving unified credit plan, divided funds, realized loan and deposits, establishing a reserve requirement system, and mutual financing". Through "divided funds" the PBoC divided funds with specialized banks. The specialized banks' own funds and other credit funds are approved by the PBoC head office for these specialized bank's running funds. Banks have autonomous management and independent accounting. Specialised banks and other financial institutions raise funds from society to fund their main part of their credit and lending operations to meet requirements of the PBoC. "realised loan and deposits" meant the funding relationship between the PBoC and other financial institutions transferred from PBoC setting plan targets for other institutions to debtor-creditor relationship. Specialised banks and other financial institutions should set up loan and deposit accounts in the PBoC. The specialized banks shall submit a certain proportion of their total deposit absorbed to the central bank as the deposit reserve and the PBoC adjust this proportion. "mutual financing" means allowing inter-bank lending and borrowing among financial institutions. This second stage of China's credit market reform marks an important step: In allowing banks to engage in own fund-raising operations and developing an inter-bank market, it paves the way towards the introduction of a fractional reserve system.

From 1994 to 1997, this evolved into a system of "total control, proportion management, classification guidance, market integration". From 1998, instead of controlling on the loan quota, the PBoC started a new credit management system on the basis of carrying out asset-liability ratio management and risk management for the state-owned commercial banks. The new system includes "planning and guidance, self balance, proportion management, indirect management", which gives more freedom to commercial banks for lending. Further measures were then taken to reform the credit plan management system which featured "centralized management on deposits and loans", eliminate caps on credit scales, gradually establish the M2 money supply since 2007 as the intermediate target of monetary policy, and develop in due time indicator of aggregate financing to the real economy as an important source of reference for monetary policy.

1.3.4 Monetary policy and financial market reform after 2008

Since 2008, the financial sector has undergone more changes, trigged by the impact of the global financial crisis. During this period, the main objective was to regulate the financial market, as well as to optimize resource allocation. The changes towards a market driven banking system, required corresponding changes in monetary policy. While the PBoC initially closely monitored banks activities to implement monetary policy directly through banks operations, the system gradually shifted (and is still shifting) to a more incentive based

system, where the PBoC acts mostly through open market operations. In its policy the PBoC traditionally heavily emphasized the role of monetary aggregates, and is only slowly moving to a stronger focus on interest rates. As of 2017 there was no single benchmark policy rate, but a range of instruments, such as target rates for loans, deposits, mortgages and a rate for repurchase operations, PBoC's open market operations with banks.

The main purpose to reform the ownership structure of state-owned banks is to establish market-oriented mechanism of commercial banks and modern corporate governance structure; and to make profit-oriented business objectives. Through the reforms of restructuring finance, introducing strategic investors and public listings, Chinese state-owned banks have had diversification of property rights based on state control. This implied further changes to bank's corporate governance, establishing frameworks and bodies such as shareholders' general meeting, board of directors, board of supervisors, and senior managers as well as a preliminary basic framework of corporate governance, taking a customer-focused, market-oriented view, to develop long-term interests of stakeholders as target. The financial reform went through substantial financial areas from 2013. For example, China eased most of the interest rate restrictions by gradually expanding the floating range of deposit and loan rates after the global financial crisis in 2008, by completely removing restrictions on loan rates of financial institutions in July, 2013 and by lifting the cap of deposit rates in October, 2015, all of which marked significant breakthroughs in China's market-based interest rate reform (see speech of Mr Yi Gang, December 2018); the government has allowed the establishment of some publicly listed banks in Hong Kong (Bailey et al., 2011), and has also loosened foreign ownership ceilings to allow foreign investors to take minority ownership stakes in the state-owned banks (Bailey et al., 2011). Lardy (2008), Cheng and Degryse (2010) and Firth et al. (2009) also show some evidence of further transformation of China's banking sector, involving gradual liberalisation to build up a commercial culture, reduce state interventions, attract better quality personnel, and foster further opening towards foreign institutions.

Summary of Chinese financial market reforms. Since the introduction of the reform and opening-up policy, a modern financial market system has been broadly established which, adapting to the socialist market economy with Chinese characteristics (see speech of Mr Yi Gang, December 2018). A multi-level and multi-type financial system including the PBoC, policy banks, state-owned commercial banks, joint-equity commercial banks and city commercial banks etc. has been established; meantime, the security market develops along with the establishment of Shanghai and Shenzhen Stock Exchanges; the monetary policy regulatory mechanism is gradually shifted from direct adjustment-oriented to indirect regulatory mechanism, which is illustrated by shareholding reforms and listing of state-owned

banks, the credit management reforms and liberalization of interest rates etc. We will look at individual banking interactions post-crisis in more details in Chapter 3.

1.4 Organization of the thesis

After this introduction there are three substantive chapters and a conclusion. Each substantive chapter includes: an introduction to the question which explains why it needs to be investigated; a literature review identifying research gaps; a description of the data and variables; a description of the methodology; a review of the findings; and some conclusions. Chapter 2 provides the basic description of the data and context, exploring the characteristics of credit cycles and explores the relations of credit cycles with policies and political conferences. Chapter 3 adopts a microeconomic perspective looking at the role of bureaucratic and economic factors in determining bank lending by 14 banks. Chapter 4 adopts a macroeconomic perspective looking at the macroeconomic interactions between money and other variables. Chapter 5 concludes with a summary of the results, the contributions they make to the body of research and the implications they have in practice, before looking ahead to possibilities for further research.

Chapter 2

Credit Cycles in China

2.1 Introduction

The crisis that started in 2007 was not only been a painful reminder of the importance of financial cycles, it also exposed our limited knowledge of them and their linkages to business cycles (Claessens et al., 2014). Credit volume is a key indicator of financial cycles.[1] As noted in the introduction, the unprecedented growth of the Chinese economy was matched by an equally unprecedented credit expansion. Some claim that this credit expansion, while it may be an important driver of Chinese development, is fundamentally unsustainable. In such a narrative China might even be perceived as a threat to the global economy: "When in doubt over the past 10 years, it has made sense to blame China" (Authers, 2018).

Given this global significance of Chinese credit, we investigate the sources of Chinese credit cycles and the degree to which credit cycles are driven by policy and the state. This chapter is largely a historical analysis of credit and money, with some discussion of the patterns of interaction with other macro variables. The quantitative analysis of these macroeconomic interactions is in later chapters. The questions we consider in this chapter are:

- How to measure credit, cycles and booms?
- How did monetary and financial policies evolve after 1978?
- What were the main features of the Chinese credit cycles after 1978?

[1] Housing price is another key variable to measure financial cycles. Claessens et al. (2014) also consider equity prices when they measure financial cycles. See Filardo et al. (2018) and Rünstler et al. (2016) for more discussions about financial cycles.

- To what extent were Chinese credit cycles influenced by the state including through monetary policies and big political conferences?

To answer these questions, we proceed as follows: Section 2.2 reviews the literature. Methods used to identify credit cycles and booms are discussed in Section 2.3. Section 2.4 gives an overview of raw data and monetary policies and identifies China's credit cycles and booms. Section 2.5 measures monetary policies and political conferences and explores their relationships with credit and money. Section 2.6 concludes.

We find that although credit, loans, and money are quite distinct concepts, in practice, they move together very closely in China over 1979Q1-2018Q1. Our threshold method shows clustered boom peaks in 1987, 1993 and 2009. This matches the pattern shown by growth rates of money and credit so is quite robust to the measures of cycle and threshold used. Most booms have longer downswing than upswing phases, which may be partly explained by the idea of a "soft" landing of the economy. Most of credit and money booms peak in important conference years or within a year after the Two Sessions. Credit and money generally go up before the Two Sessions and go down after. However, this is a qualitative rather than an exact quantitative relationship because not all cycles are the same. There is some evidence for a counter-cyclical monetary policy stance. This careful analysis of the data and history is an essential foundation for the quantitative analysis in later chapters. These findings may have implications for the design and conduct of macroprudential policy, but these policy issues involve political judgments which are beyond the scope of the thesis.

We use two credit measures: domestic credit and claims on private sector to identify China's credit cycles.[2] The analysis of credit cycles can be based either on growth rates or a trend-cycle decomposition. There is considerable controversy over methods to extract cyclical components from observed data. Gourinchas et al. (2001) and Mendoza and Terrones (2008, 2012) employ Hodrick and Prescott (1997) (HP) filter to isolate credit cycle fluctuations in the data. But the HP filter has problems. There is no agreement on how to choose the smoothing parameter, λ. It can introduce spurious dynamic relations, see Hamilton (2018). Baxter and King (1999) suggest a band-pass filter, which we use. On the basis of credit cycle series, we further use a threshold method to identify credit booms, which allows a better understanding of credit cycles.

Credit refers to the ability to borrow. In China, domestic credit is mainly supplied by financial institutions through loans (assets of financial institutions), while most financial institutions strongly rely on deposits (liabilities) to support their lending. Money refers to holdings of cash and deposits. Credit expansion in China historically has been accompanied

[2]Claims on private sector refers the domestic credit supplied to the households and all resident non-financial enterprises including public-owned, private-owned, and foreign-controlled non-financial enterprises.

by an expansion of broad money. So, the study of monetary aggregates such as broad money gives another perspective to view credit cycles.

2.2 Literature review

2.2.1 The role of money and credit

The economic thinking about the role of money and credit in the macroeconomy has changed substantially over time Freixas and Rochet (1997, chap. 6). There is no consensus about the role of the financial sector in economic growth. Schularick and Taylor (2012) concluded that credit has progressed from an "irrelevance view", which suggests it is independent of real economic decisions, to a "credit view", which suggests credit matters for economic growth.

Schularick and Taylor (2012) stated that, "in the late twentieth century the "credit irrelevance view" gained influence, associated with the ideas of Modigliani and Miller (1958) among others, where real economic decisions became independent of financial structure altogether". In the standard real business model and the standard Keynesian text IS-LM model, it is assumed that there is no friction in the credit market, and hence credit market conditions do not affect macroeconomic outcomes (Hofmann, 2001). Till in the late 1980s, the "credit view" gradually attracted attention and adherents, but economists disagree sharply about the role of the financial sector in economic growth. Levine (2005) concluded that,

> "Economists disagree sharply about the role of the financial sector in economic growth. Finance is not even discussed in a collection of essays by the "pioneers of development economics" (Bauer et al., 1984), including three Nobel Prize winners, and Nobel Laureate Lucas (1988, p. 6) dismisses finance as an "overstressed" determinant of economic growth. Robinson (1952, p. 86) famously argued that "where enterprise leads finance flows". From this perspective, finance does not cause growth; finance responds to changing demands from the "real sector"".
>
> "At the other extreme, Nobel Laureate Miller (1998, p. 14) argues that, "[the idea] that financial markets contribute to economic growth is a proposition too obvious for serious discussion". Drawing a more retained conclusion, Bagehot (1873), Schumpeter (1912), Gurley and Shaw (1955), Goldsmith (1969), and McKinnon (1973) reject the idea that the finance growth nexus can be safely ignored without substantially limiting our understanding of economic growth".

In the survey of Levine (2005), he finds a preponderance of research supported that both financial intermediaries and markets are important for economic growth. Bernanke and Blinder (1988) relaxed the assumption of frictionless credit market and produced a separate role of credit in economic activity. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) develop this modified real business cycle models and think that due to informational asymmetries in credit markets, there is a mutually reinforcing interaction between credit and macroeconomic activity, which is referred to as the "financial accelerator" by Bernanke et al. (1996). From the perspective of "financial accelerator", due to informational asymmetries in credit markets, firms and households facing borrowing constraints can only borrow when they offer collateral, which depends on their net worth. Their net worth is procyclical, and hence credit is procyclical. It means that credit is not only positively related to economic activity but can propagate and amplify the business cycles. Emprically, Sharif (2010) investigated the impact of bank lending supply fluctuations on economic activity in a multitude of developed and developing countries using an unrestricted VAR model for the 1997-2006 monthly data, and they find that bank loan supply fluctuations have a direct impact on output and they are transmitted into the economy, which supports for the already existing findings by Friedman et al. (1993) and later Walsh and Wilcox (1995). Therefore, credit matters for the economy.

Economists have devolved a substantial amount of attention to credit booms. There are some empirical papers comparing credit booms in industrial and emerging countries such as Tornell and Westermann (2005) and Mendoza and Terrones (2008, 2012), or do a comprehensive study on credit booms at a regional level. These authors focused on common features of credit fluctuations shared by groups of countries or regions. Even though some studies such as Tornell and Westermann (2005), Dell'Ariccia et al. (2007), Mendoza and Terrones (2012) and Arena et al. (2015) included China in their samples when they studied credit booms in emerging markets, it is not far enough to understand China's credit booms. China, as a big economy in the world, shows many differences in its credit and monetary policies with the rest of the world. It is valuable to study credit booms in China as a separate case.

2.2.2 Methods to identify business cycles.

Burns and Mitchell (1946) developed a method (analysis of turning points) for measuring business cycles that could be used widely in matter of differences in countries or sample periods. They focused on changes in levels of economic activity tracking absolute declines and increases. Their method involved a large number of variables and a lot of judgment. It remains the basis of the NBER business cycle dating procedure. Bry and Boschan (1971) provided the so-called BB algorithm to identify turning points in the log-level of a

macroeconomic series. BB algorithm was then extended by Harding and Pagan (2002) to BBQ algorithm which was then employed by Claessens et al. (2012) to identify financial cycles. BB algorithm can also be developed to replicate the NBER methodology to identify local maxima subject to constraints on the minimum duration of the cycle. We call these methodologies used to identify business cycles based on research of Burns and Mitchell (1946) and Bry and Boschan (1971) as "classical methodology".

But Baxter and King (1999) criticized the method provided by Burns and Mitchell (1946), due both its complexity and its central element of judgment. Various new techniques to extract business-cycle components from time series are developed by modern empirical macro economists. Examples of these techniques are summarized by Baxter and King (1999) and Kaminsky and Schmukler (2008) like the application of two-sided moving average, first differencing, removing of linear or quadratic time trends, the HP filter, the band-pass filter, and the Markov switching model which was used by Maheu and McCurdy (2000). We call these new techniques to measure business cycles as "modern methodology". Baxter and King (1999) testified that linear detrending and first-differencing filters do not have enough ability to isolate business-cycle fluctuations in the data. Moving-average analysis can only in some cases produce reasonable approximations to an ideal business-cycle filter.

Despite much research on pattern recognition methods being used to date business cycle turning points, we should take care when we use these methods and same criteria to identify credit cycles because of differences in business cycles and financial cycles or credit cycles. Researchers like Burns and Mitchell (1946) and Baxter and King (1999) specified that business cycles were cyclical components of no less than six quarters (eighteen months) in duration and last fewer than 32 quarters (eight years). Business cycles are measured by a range of economic indicators including money supply (M2), interest rate spreads, the value of outstanding commercial and industrial loans, and the ratio of consumer credit outstanding to personal income. Rummel (2018) argued that both theoretical and empirical work suggest that the business and financial cycle are separate economic phenomena, operating at different periodicities. For example, Drehmann et al. (2012) defined the financial cycle is much longer than the traditional business cycle. Rummel (2018) found that a spectral analysis of the frequency components shows that most credit cycles have a lower frequency bound close to – or below – the minimum stylised duration of eight years proposed by Drehmann et al. (2012).

In our study, we assume that credit cycles have the same length as business cycles (cyclical components of no less than six quarters in duration and last fewer than 32 quarters). Some of the indicators for measuring business cycles are related to money and credit which are also macroeconomic indicators. So it will be fine to use the same procedure and criteria to identify credit cycles as to business cycles. Using same procedure and criteria makes

the relation between credit and business cycles comparable, and it becomes possible to build links between them. Another point is our short sample period is more suitable to this assumption of length of cycles. Claessens et al. (2012) identified financial cycles using the same methodology as used to determine business cycles.

2.2.3 Methods to identify credit cycles and booms

After cyclic fluctuations are identified in the credit data, following Gourinchas et al. (2001), henceforth GVL, a threshold method is then used to identify credit booms based on cycles. So, credit booms are identified by comparing a country's credit to its trend. GVL measured private credit as claims on the non-banking private sector from banking institutions. They used HP filter with smoothing parameter set at 1000 to 91 countries (China is not included.) over the period 1960-1996, with a special focus on Latin American, to identify credit cycles. They then considered two alternative threshold definitions: relative deviation and absolute deviation, to identify credit booms. The former is based on the relative difference between the actual and predicted credit-to-GDP ratios. Mendoza and Terrones (2008, 2012) developed the threshold method and used it to identify credit booms in industrial and emerging economies. They define an episode as a credit boom when the amount of credit extended by the banking system to the private sector grows by more than that experienced during a typical cyclical expansion. Specifically, a country experiences a credit boom when the deviation in (log) real credit per capita from its long-run trend exceeds the standard deviation of the cyclical component by a factor of 1.65. Arena et al. (2015) computed the long-run trend of real credit per capita using the HP filter, and followed the criteria outlined in Mendoza and Terrones (2012) to identify credit booms in low-income countries.

Tornell and Westermann (2002) used HP filter with parameter set at 100 to identify lending cycles from 1980 to 1999 in 39 middle income countries. They characterized the boom-bust cycle by means of an event study and further shifted attention to lending booms. Tornell and Westermann (2002) stated that,

> "Many papers look at deviations from a Hodrick-Prescott filter rather than growth rates. This has the advantage of having a more flexible trend and a corresponding definition of cycles. However, the HP filter can be a poor indicator of the trend, if there are structural breaks in the beginning or the end of the period, in particular if the sample is very short. We therefore look at both, growth rates and deviations from the HP-trend. ⋯ While the growth rates are easily comparable across countries, the levels are not due to different long-term trends, structural

> breaks, etc. (unless they represent the level of a ratio, such as credit/deposits or credit/GDP). The HP-trend is therefore a trend corrected proxy for the levels".

Mendoza and Terrones (2008) developed the trend-based threshold methodology and found that it was successful at identifying credit booms with a clear cyclical pattern in both macro and micro data. Elekdag and Wu (2013) used similar threshold method but with a different threshold value to identify credit booms, which are broadly periods of excessive credit growth, based on 1960-2010 annual macroeconomic, financial, corporate- and banking-level data in 21 advanced and 43 emerging economies, and they identified 99 credit booms across these economies. Mendoza and Terrones (2012) used HP filter with parameter set at 100 to get the credit cycle series, then applied this threshold method to data for 61 countries (21 industrial countries, ICs; and 40 emerging market economies, EMs) over the 1960-2010 period. Their measure of credit is the sum of claims on the private sector by deposit money banks (IFS line 22d) plus, whenever available for the entire sample period for a given country, claims on the private sector by other financial institutions (IFS line 42d). China is a sample country in their paper, but they did not find any credit boom in China. Arena et al. (2015) applied the Mendoza and Terrones (2012) methodology to a comprehensive database on bank credit, covering 135 developing countries over the period 1960–2011. China is also a sample country in Arena et al. (2015)'s paper, and they did not find credit booms happening in China.

There are some differences between research in credit measurement and methodology to isolate cycles. There are also differences in how to define credit and credit booms, how to identify credit booms, and what proper threshold values are. Consequently, researchers get inconsistent conclusions sometimes. For instance, using different measure of credit and threshold factors, Mendoza and Terrones (2012) find that in both emerging and industrial countries, credit booms are associated with a well-defined cyclical pattern in output and expenditures, but this contrasts sharply with the findings of Gourinchas et al. (2001), showing only ambiguous evidence of this association in Latin America. Mendoza and Terrones (2012) find that credit booms normalized by the cyclical variability of credit are similar in magnitude across industrial and emerging economy, which is different from the findings of Mendoza and Terrones (2008). Different from their previous work, Mendoza and Terrones (2012) use a year-end stock credit variable, expand the data to 2010 rather 2006, and include a sample of 61 countries rather 48.

Comment. The majority of previous empirical research focuses on credit cycles and booms in different groups of countries or regions, for example, industrial and emerging countries, low income countries, Latin America, and Asia. Few researchers focus on credit cycles and booms in a certain country including China. HP filter is commonly used to

identify credit cycles, but there are some specific differences, for example, in filter parameter. Researchers use different thresholds, for example, trend-based threshold and growth-based threshold, to identify credit booms. So there is no consistent method to identify credit cycles and booms. Against this background, this chapter is to find proper methods to identify credit cycles and booms and explore the credit features in China.

2.3 Methodology

2.3.1 How to measure credit

This chapter aims to study credit cycles and booms in China. The credit variables we mainly study are: domestic credit (DC) and claims on private sector (CLP) in real terms. To view credit cycles from another perspective, we also study money variables: broad money (M2) in real term. All these variables are financial variables. We discuss them in detail in Section 2.4.

2.3.2 How to isolate credit cyclic fluctuations in data

We have summarized methods used to identify financial cycles and discussed the definition of financial cycles in the literature review section. The financial cycle can be characterised empirically using approaches: analysis of turning points and frequency-based filters. We mainly focus on frequency-based filters: band-pass filter and HP filter.

In the frequency domain, any time series within a broad class can be decomposed into different frequency components (Christiano and Fitzgerald, 2003). A macroeconomic time series can be decomposed into very slow-moving ("trend") components and very high-frequency ("irregular") components while retaining intermediate ("business cycle") components (Baxter and King, 1999). The spectral theory supplies ideal band pass filter to decompose these components. The ideal band pass filter requires infinite data, while the macroeconomic data is usually finite. Therefore, some researchers have tried to construct a good approximation to the optimal filter, for example, band pass approximation based on regression data on sine and cosine functions (Trigonometric Regression filter) (Christiano and Fitzgerald, 1998; Hamilton, 1994, p.158-63), band pass filtering approach recommended by Baxter and King (1999) (BK filter), Random Walk filter developed by Christiano and Fitzgerald (2003) (CF filter). We have known that researchers like Arena et al. (2015) used HP filter isolate credit fluctuations in data. Abbasoglu et al. (2015) and Mimir (2016) also used HP filter to investigate the cyclical components of bank balance sheet items and real variables, as HP filter is the most common filtering method in the business cycle research. But in the study of Mimir (2016), they used the log-linearly detrended series of real and financial

variables rather than HP-filtered series, because it is commonly argued in the literature that HP filter cannot capture the dynamics of series in the beginning and at the end of sample time period well.

Baxter and King (1999)'s investigation suggested the HP filter does not really generate as many useful estimates of the cyclical component as there are data points, although Hodrick-Prescott filtering can, in some cases, produce reasonable approximations to an ideal business-cycle filter. However, the optimal approximate band-pass filter that Baxter and King (1999) developed is more flexible and easier to implement than HP filter and produces a better approximation to the ideal filter. Baxter and King (1999) argued that their high-pass filter is better to data sampled at other-than-quarterly frequencies for its ease of application. For high-pass filter, Baxter and King (1999) think that it is clear how to move between different data frequencies for their procedures. However, it is much less clear how to proceed with the Hodrick and Prescott (1997) method, because it requires the research to specify the "smoothing parameter", λ. For quarterly macroeconomic data, Baxter and King (1999) recommend the Burns-Mitchell band-pass filter, which admits frequency between 6 and 32 quarters, with maximum lag length 12. For annual macroeconomic data, they found that band-pass and high-pass business-cycle filters are equivalent and accordingly recommended a single filter that admits periodic components between two and eight years, with given maximum lag length 3. Tornell and Westermann (2002) stated that, "Many papers look at deviations from a HP filter rather than growth rates. This has the advantage of having a more flexible trend and a corresponding definition of cycles. However, the HP filter can be a poor indicator of the trend, if there are structural breaks in the beginning or the end of the period, if the sample is very short". Christiano and Fitzgerald (2003) concluded that the HP filter appears to do just fine on the business cycle and higher-frequency components of quarterly data. However, Christiano and Fitzgerald (2003) think that the band pass filter can not only handle what the HP filter is good at, but can do a good work in other frequency components of the data; in daily, weekly, monthly, or annual data; or in real-time trend estimates. Comparing several band pass filters, Christiano and Fitzgerald (2003) found that BK filter, Trigonometric Regression filter, and Random Walk filter makes little difference for applications that involves the business cycle and higher-frequency components of the data. However, the Random Walk filter outperforms BK filter and trigonometric filter for lower-frequency components.

Furthermore, we should mention the filtering methods in the time domain. Beveridge and Nelson (1981) (BN) introduced a general methodology to carry out the trend-cycle decomposition depending only on past data. The BN decomposition implies a very high signal-to-noise ratio in terms of the variance of trend shocks as a fraction of the overall

quarterly forecast error variance for output growth, while the estimated output gap is with small amplitude and lack of persistence. Kamber et al. (2017) argued that imposing a low signal-to-noise ratio would generate more intuitive estimated output gap in the sense of being large in amplitude, persistent, and moving closely with the NBER reference cycle. Kamber et al. (2017) constructed the BN decomposition by imposing a low signal-to-noise ratio on an AR model, and referred their approach as BN filter. They argued that the other methods like the HP filter and the band pass filter can produce similarly intuitive estimates of the output gap but are far less reliable in terms of their revision properties. BN filter has not got its popularity in isolating business cycles.

Summary. There would be little reason to prefer HP filter rather than band-pass filter. We prefer to employ the BK filter for quarterly data, which admits periodic components between 6 and 32 quarters with maximum lag length 8. We use maximum lag length 8 rather than 12 to capture more dynamics of series in the beginning and at the end of sample period.

2.3.3 How to identify credit booms

Most researchers define a credit boom as a period in which credit grows above a threshold value. For example, Mendoza and Terrones (2008) define "a credit boom as an episode in which credit to the private sector grows by more than a threshold during a typical business cycle expansion". Dell'Ariccia et al. (2007) "classify a country-year as experiencing a credit boom if Bank Credit to the Private Sector as a share of GDP grows at more than 10 percent". They also vary this numerical threshold to check robustness. Dell'Ariccia et al. (2007) also identify credit booms by examining whether the actual rate of growth of credit in an economy-as measured by Bank Credit to the Private Sector ratio-appears abnormally high relative to its previous trend. Dell'Ariccia et al. (2014) define "a "credit boom" as an episode in which the ratio of credit to GDP grows faster than what is implied by its trend, which follows the normal pace of credit growth in that particular country. An episode of rapid credit growth is marked as a boom when the deviation from trend exceeds a country- and path-dependent or ad hoc threshold".

Although the above definitions of credit booms are different in detail, they are essentially the same: a credit boom is broadly a period of excessive credit growth in which credit grows by more than a threshold. So, defining a credit boom includes three main parts: how to measure credit, how to construct boom thresholds, and how to set threshold values to identify the start, peak, and end of a credit boom. We will investigate these questions in following sections.

2.3.3.1 Credit variable forms

This section mainly discusses why we do not mesure credit cycles on the basis of credit-to-GDP ratio (credit ratio), which were commonly used.

GVL use HP filter to isolate cyclic fluctuations in the credit ratio, and then identify credit booms based on the cycle series. The difference between credit ratio and its long-term trend is defined as the credit-to-GDP gap (credit gap). The credit gap is a useful early warning indicator for banking crises (e.g. Borio and Drehmann, 2009; Borio and Lowe, 2004; Claudio and Lowe, 2002; Nithesh, 2017)

The Basel III uses this gap as a guide for setting counter-cyclical capital buffers. There are many practical and conceptual criticisms of Basel III using the credit gap as a guide. However, by reviewing the main criticisms, Drehmann and Tsatsaronis (2014) argue that, the credit gap's "usefulness must be judged exclusively on whether it provides policymakers with reliable signals about when to raise the buffer. ⋯ the credit-to-GDP gap is on average (across many countries and several decades) the best single indicator ⋯, including for emerging market economies. This does not mean that there are no composite indicators that may perform better, or single indicators that may provide clearer signals either in the context of individual countries or at particular points in time".

Dell'Ariccia et al. (2014) conclude both the positive and negative sides by looking at the credit ratio rather than credit itself. On the positive side, for example, credit ratio relates credit developments to the size of the economy and accounts for the procyclicality of credit. It makes credit comparable among countries. On the negative side, for example, the methodology may erroneously tag an observation as a credit boom when the credit ratio jumps up not because of an increase in credit but because of a decrease in GDP, and Dell'Ariccia et al. (2014) manually check such cases and drop them from the list of booms. Mendoza and Terrones (2008) argue that using credit ratio has three limitations. One is that it does not allow for the possibility that credit and output could have different trends, which is important if countries are undergoing a process of financial deepening, or if for other reasons the trend of GDP and that of credit are progressing at different rates. Second, there can be situations when both nominal credit and GDP are falling and yet the ratio increases because GDP falls more rapidly. Lastly, when inflation is high, the fluctuations of the credit to GDP ratio could be misleading because of improper price adjustments. Therefore, Mendoza and Terrones (2008, 2012) and Arena et al. (2015) use real credit per capita to measure credit. They also use a credit boom threshold, which are proportional to each country's standard deviation of credit over the business cycle, to reflect differences in country size, which makes comparison of credit booms across countries feasible.

Comment. What matters is not only the indicator itself, but also what it is used for. Different forms of financial variables are used for different purposes. For example, Credit at current prices can be used to explain nominal credit changes, while credit deflated by CPI to explain real credit changes; and credit per capita reflects credit booms at a per capita level, while credit ratio measures credit as share of GDP. One cannot say that one variable is better than another. But given the argument of credit ratio, we isolate credit cycles based on real credit level series. We then identify credit booms based on real credit cycles and growth series by a threshold method which reflects China's economy facts.

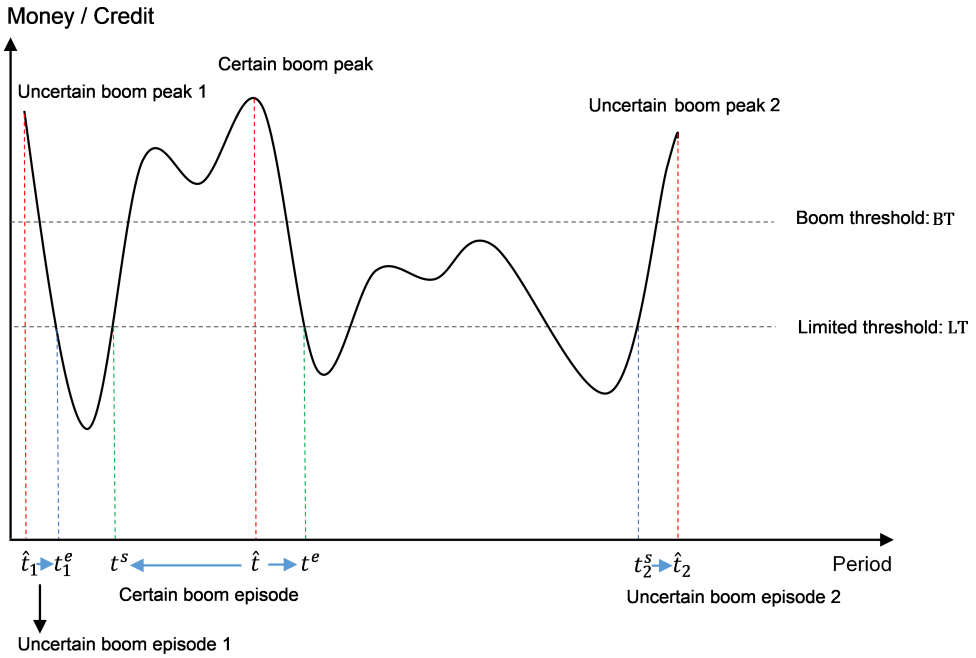
2.3.3.2 Formalization of credit booms

We have discussed the threshold method used to identify credit booms in the literature review section, for example, trend-based threshold and growth-based threshold. This section discusses more details about how to construct a "boom" threshold method using the trend-based threshold as an example. Our formalization for definition of credit booms is on the basis of ideas in the papers of Mendoza and Terrones (2008, 2012). This study is different from the previous research in how to deal with the ending observations of a series and how to choose proper boom threshold values.

To define a credit boom, the first step is to measure credit, then to isolate cyclic fluctuations in data by filters, and then to identify credit booms including boom peaks and durations by thresholds. Based on credit cycle series, we use a boom threshold (BT) to identify boom peaks, a boom starting threshold (BST) to identify the start of a boom, and a boom ending (BET) threshold to identify the end. To formalize the definition of a credit boom, denote the financial series in country i, date t as x_{it}. Country i is defined to have experienced a credit boom when one or more contiguous dates for which the credit boom condition $x_{it} \geq BT$ holds. Figure 2.1 shows how the boom peak and duration for a certain financial series are identified. The boom peaking date, $\hat{t}$, is a date that shows the maximum difference between financial series, x_{it}, and boom threshold, BT. Given $\hat{t}$, the boom starting date, t^s, is a date such that $t^s < \hat{t}$ and t^s yields the smallest difference, $|x_{it} - BST|$, and the ending date, t^e, is a date that yields the smallest difference, $|x_{it} - BET|$. We call both the boom starting and ending thresholds as boom limited threshold, LT, and set $BST = BET = LT$. Once the starting and ending dates are set, the difference, $t^e - t^s$, gives the duration of the credit boom. Following formular shows credit boom definition clearly. The credit boom peak, $\hat{t}$, satisfies,

$$max|x_{it} - BT|.$$

Fig. 2.1 Boom definition.



Note: The solid black curve can be any cyclical credit or money, or any growth of credit or money.

The starting date, t^s, of the credit boom satisfies,

$$min|x_{it} - BST|, BST = LT.$$

The ending date, t^e, of the credit boom satisfies,

$$min|x_{it} - BET|, BET = LT.$$

The credit boom duration is,

$$t^e - t^s.$$

We cannot determine whether the starting and ending observations of a credit cycle series is a boom, so we separate booms into certain and uncertain booms, boom peaks into certain and uncertain boom peaks, and boom durations into certain and uncertain boom durations. Figure 2.1 and figures in Appendix A.1 show several examples of certain and uncertain booms. In Figure 2.1, $\hat{t}$ gives a certain boom peak date and the difference, $t^e - t^s$, gives the duration of this certain boom. $\hat{t_1}$ gives a uncertain boom peak date and the difference, $t_1^e - t_1^s$, gives the duration of this uncertain boom. Later we will include uncertain boom peaks and durations in the case of China.

2.3.3.3 Threshold values

Gourinchas et al. (2001) choose boom threshold values according to the number of boom cases yielded. Somewhat arbitrarily, they choose the limit threshold values. Mendoza and Terrones (2008, 2012) set threshold values as a proportion (threshold factor) of each country's standard deviation of credit over business cycle, so the threshold values can vary across countries and, hence reflect country's heterogeneity. Denote the deviation from the long-run trend in the logarithm of real credit per capita in country i, date t as l_{it}, and the corresponding standard deviation of this cyclical component as $\sigma(l_{it})$. Denote the boom threshold factor as ϕ_b, the boom starting threshold factor as ϕ_s, and the boom ending threshold factor as ϕ_e. Country i is defined to have experienced a credit boom when one or more contiguous dates for which the credit boom condition $l_{it} \geq \phi_b \sigma(l_{it})$ holds. The baseline boom threshold factor ϕ_b is set at 1.65, because the 5 percent tail of the standardized normal distribution satisfies Prob($l_{it}/\sigma(l_{it}) > 1.65$)=0.05. They also conducted robust analysis by setting ϕ_b to 1.5, 2 and found that the main results are robust for 1.65. It is necessary to conduct sensitivity analysis for the threshold factors, because boom cases are possibly sensitive to boom threshold factors. They use a limited threshold factor set at 1 ($\phi^s = \phi^e = \phi_l = 1$), so the limited threshold value is $\sigma(l_{it})$.

Later we will see that if we follow the approach of Mendoza and Terrones to identify China's credit booms. If we set the baseline boom threshold factor ϕ_b at 1.65, only few extreme credit boom cases are identified. Instead, whether it is based on real credit cycles or growth, we find that a boom threshold, mean plus standard deviation of credit series, and a limited threshold, mean of credit series, can identify most boom cases in China.

2.4 Data

This section gives an overview of the data employed in the empirical analysis of this chapter. For this we first evaluate and explain of monetary policy conduct in China, to then derive our policy measures and filters used to extract cyclical components and identify boom periods. We evaluate the evolution of credit and monetary aggregates based on the following measures: domestic credit (DC), claims on private sector (CLP), and broad money (M2). Credit refers to the ability to borrow, and money refers to holdings of cash and deposits. In principle although they are distinct, in practice they are closely linked. The monetary authorities control money and credit through various instruments: interest rates, requirements on banks, such as reserve requirement ratio, lending quotas, and indirect controls on lending known as window guidance. To show the relations between credit and monetary policy, we collect data of benchmark deposit interest rate (DINR), and benchmark lending interest rates (LINR),

and reserve requirement ratio (RRR). To express interest rates in real terms, we also collect inflation data based on the Consumer Price Index (CPI). The main databases are Datastream (DS), CEIC (Global Economic Data, Indicators, Charts & Forecasts) data, the Bank for International Settlements (BIS) data, MR (Mohaddes and Raissi, 2018) data, and PPI data.[3] Table 2.1 presents details regarding source and data availability for each variable.

2.4.1 The conduct of Chinese monetary policy

2.4.1.1 Nominal interest rates and reserve requirement ratio

The People's Bank of China (PBoC) targets a set of interest rates. Deposit interest rates are paid by commercial or similar banks to deposit account holders. Lending interest rates are usually determined by the short- and medium-term financing needs of the private sector. The lending rate is normally differentiated according to creditworthiness of borrowers and objectives of financing. The People's Bank of China sets benchmark deposit and lending rates directly. At the same time, it sets upper limit of the floating range of deposit interest rates of financial institutions, the deposit rate multiplier times the benchmark deposit interest rate, as well as the lower limit of the floating range of loan interest rates, the lending rate multiplier times the benchmark lending interest rate. The rate multipliers changed several times since China introduced economic reforms in 1978. The reserve requirement ratio is the portion of reservable liabilities that depository institutions must hold onto, rather than lend out or invest. In 1984, the PBoC established a statutory reserve requirement system while it started to independently exercise the central bank's functions. Reserve requirement ratio is one type of monetary policy rates. The PBoC can regulate lending to the private sector by controlling the availability of credit through changes in the reserve requirements imposed on banks and ceilings on the credit provided by banks to the private sector. The relationship between PBoC, financial institutions, non-financial enterprises, and households are outlined in Figure 2.2.

Figure 2.3 shows the benchmark interest rates and reserve requirement ratio series in China. The deposit and lending interest rates roughly go up and down together. The interest rate spread which is the difference between lending and deposit interest rates is small from 1980M1-96M7, and it becomes larger after. The interest rate spread - the margin between the cost of mobilizing liabilities and the earnings on assets - measures financial sector efficiency in inter-mediation. A narrow spread in the early stage of economic reforms means low transaction costs, which reduced the cost of funds for investment and it is crucial to economic growth. In the early stage, Chinese government aimed to promote economy by controlling

[3] PPI, http://www.100ppi.com/mac/data—1111.html.

Table 2.1 Data and variables.

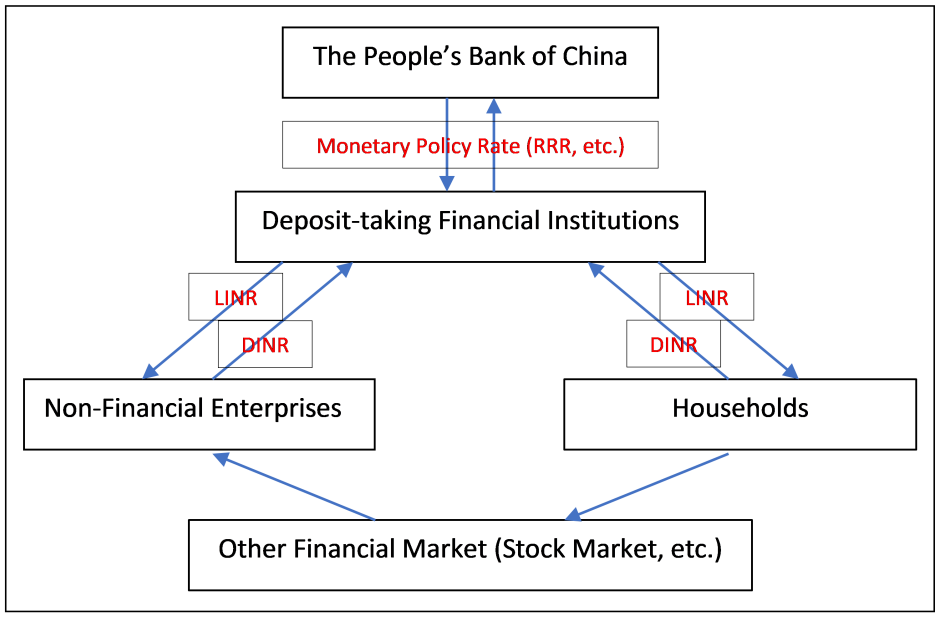
Indicator	Abbr.	Source	Unit	Prices	Seasonality	Start	End	Obs.
Banking Survey: Money Plus Quasi Money	M2	CEIC	RMB bn	CURN	NADJ	1978Q1	2018Q1	161
Banking Survey: Domestic Credit	DC	CEIC	RMB bn	CURN	NADJ	1978Q1	2018Q1	161
Banking Survey: Claims on Private Sector	CLP	CEIC	RMB bn	CURN	NADJ	1978Q1	2018Q1	161
GDP	Y	DS	RMB bn	CURN	NADJ	1980Q1	2018Q3	155
Real GDP	rY	DS	RMB bn	2010	NADJ	1980Q1	2018Q3	155
Lending Rate	LINR	CEIC	% pa	% pa	NADJ	1980Q1	2018Q1	153
Deposit Rate	DINR	CEIC	% pa	% pa	NADJ	1980Q1	2018Q1	153
Consumer Price Index	CPIo	CEIC	2010=100	2010=100	NADJ	1986Q1	2018Q1	129
Consumer Price Index (Calculated)	CPIc	DS	2010=100	2010=100	NADJ	1980Q1	2018Q3	155
Consumer Price Index (Calculated)	CPIu	MR, CEIC	2010Q1=100	2010Q1=100	SA	1979Q1	2018Q3	159
The Rate of Inflation	Dp	MR	1	1	SA	1979Q2	2016Q4	151
Deposit Rate	DINR	CEIC	% pa	% pa	NADJ	1980M1	2018M5	461
Lending Rate	LINR	CEIC	% pa	% pa	NADJ	1980M1	2018M5	461
Reserve Requirement Ratio	RRR	PPI	%	%	NADJ	1986M1	2018M10	394

Note 1: RMB bn means billions of Chinese currency, renminbi. CURN means current prices. NADJ means not seasonally adjusted series. SA means seasonally adjusted series. % pa means percent annual rates. Banking survey is the consolidation of the monetary survey and the balance sheet of specific depository institutions. Monetary survey is the consolidation of the balance sheets of the monetary authorities and the deposit money banks. Deposit money banks are the central bank and banking institutions (deposit money and specified deposit institutions). The data source is the PBoC's "All Accounts" financial reporting system.

Note 2: Section A.2 of Appendix A shows how to calculate CPIo and CPIu. We use CPIu to turn nominal terms into real terms.

Note 3: **Definition**: Financial Institutions include the People's Bank of China (PBoC), the Industrial and Commercial Bank of China, the Agricultural Bank of China, Bank of China, China Construction Bank, the State Development Bank, the Export and Import Bank of China, the Agricultural Development Bank of China, Bank of Communications, CITIC Industrial Bank, Everbright Bank of China, Hua-Xia Bank, Guangdong Development Bank, Shenzhen Development Bank, China Merchants Bank, Shanghai Pudong Development Bank, Fujian Industrial Bank, China Minsheng Banking Corporation, Yantai Housing and Savings Bank, Bengbu Housing and Saving Bank, City United Commercial Banks, Urban Credit Cooperatives, Rural Credit Cooperatives, finance companies, trust and investment companies, leasing companies and Postal Savings Bureau. **Scope**: Effective 1997, the financial statistics has been collected and reported according to the new monetary statistics indicators system. As of the first quarter of 1997, the statistics may not be fully consistent with the historical data.

Fig. 2.2 Simplified interest rate system.

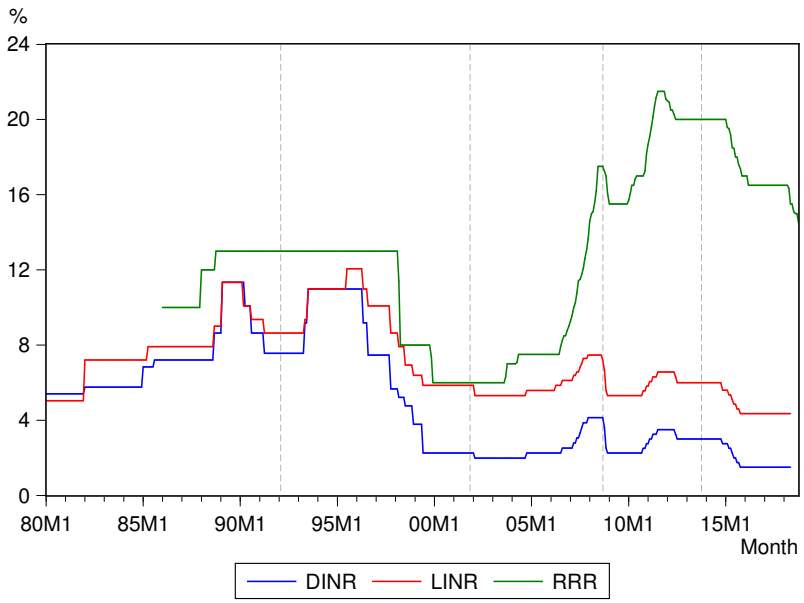


interest rates. Since 1996, China's interest rate liberalization has started gradually, and a wide spread increased the cost of funds for investment. The interest rates increased steadily from 1980M1-90M2, and were low between 1991M4-1993M4 (deposit rate is 7.56%, and lending rate is 8.64%). The deposit rate increased to a peak (10.98%) in 1993M7 and kept to 1996M4. The lending rate increased to a peak (12.06%) in 1995M7 and kept to 1996M4, which reflected high inflation in same period. From 1996 to 2003, both the deposit and lending interest rates have been falling for eight consecutive years. The deposit rate kept between 2.25%-4.14%, the lending rate between 4.35%-7.47%, and the interest rate spread between 2.85%-3.6% after 1999M5. The reserve requirement ratio was between 10% and 13% from 1986M01-98M3, decreased sharply to 6% from 1999M12-2003M9, increased rapidly to 17.5% in 2008M6 and kept above 14% after.

2.4.1.2 Real interest rates

We measure the real interest rate as a nominal interest rate adjusted for inflation as measured by the Consumer Price Index (CPI). We use both the real deposit rate, rDINR= $DINR_t - \pi_t^y$, and the real lending rate (rLINR)=$LINR_t - \pi_t^y$, where π_t^y is inflation at percent annual rates, PIu_t. Bekaert et al. (2013) regard real lending interest rate as a measurement of monetary policy stance. Figure 2.4 shows real interest rates from 1980Q1-2018Q1. They have troughs in 1988Q4 and 1994Q4 with big negative values, caused by high inflation. They show a

Fig. 2.3 Nominal interest rates and reserve requirement ratio.



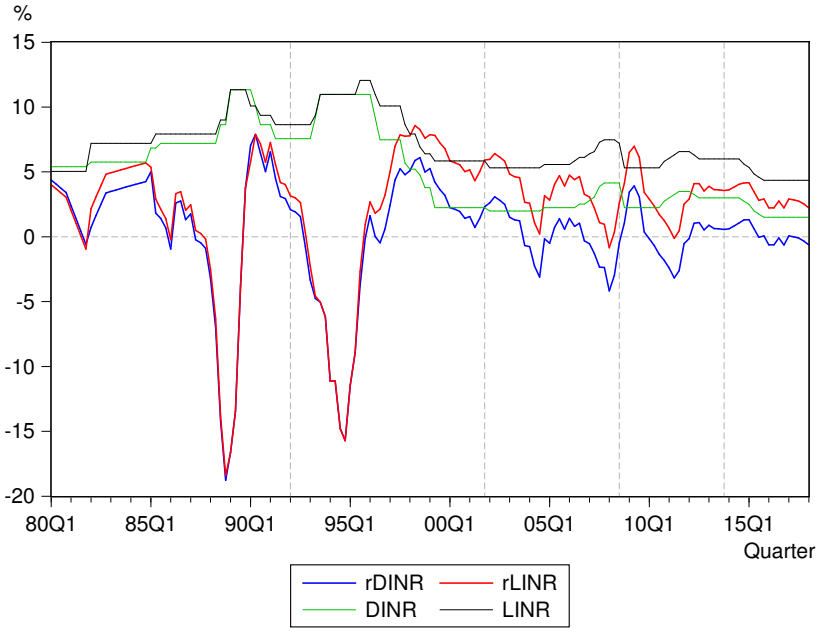
Note: DINR is the benchmark deposit interest rate for 1 year time deposit with lump-sum deposit and withdrawal. LINR is time short-term (6 months-1 year) benchmark lending interest rate.

rapid growth from 1994 to 1998 and then a downward trend till 2004. Both real lending and deposit interest rates fluctuate with a large range before around 2001 and were relatively steady after. The real deposit rate was negative in several periods, including 2003Q3-05Q1, 2006Q4-08Q3, 2010Q1-12Q1. We discuss the process of interest rate liberalisation later with Chinese monetary policy.

2.4.1.3 Inflation and interest rates

Figure 2.5 shows the Consumer Price Index and inflation from 1980Q1-2018Q1. In Section A.2 in Appendix A, we derive three Consumer Price Indexs: CPIo, CPIc, and CPIu, and annual inflation in percent annual rates: PIo, PIc, and PIu. CPIu covers a longer period and is seasonally adjusted. We will use CPIu and PIu through this chapter. The Consumer Price Index shows an increasing trend. Inflation measured by CPIu was very high in periods: 1985Q2-90Q1 (above 4.28%) and 1991Q3-97Q1 (above 4.46%). Inflation peaked over 27.97% in 1989Q1 and 26.69% in 1994Q4. But inflation fell sharply with deflation in the late 1990's. The high inflation between 1985-95 occurred because the economic reforms increased demand and the national income, causing the price of goods to go up. Meanwhile, enterprises tended to invest blindly leading to excessive investment demand.

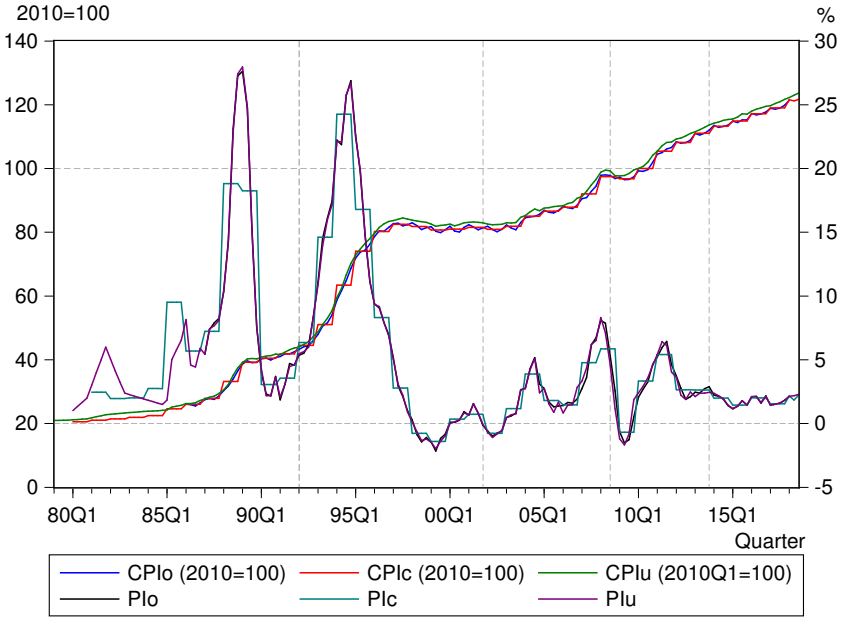
Fig. 2.4 Real and nominal interest rates.



Note: rINR is the real benchmark deposit interest rate for 1 year time deposit with lump-sum deposit and withdrawal. rLINR is real time short-term (6 months-1 year) benchmark lending interest rate.

The short-term interest rate is regarded as an instrument of monetary policy and the policy should be focused on the control of inflation by increasing short-term interest rates (Alvarez et al., 2001). The PBoC could adopt monetary policies, for example, adjusting benchmark interest rates and the floating range, to affect money supply and further inflation and output. Since 1978, the interest rate policy has gradually become an important tool for Chinese government to regulate economy. Therefore, to curb inflation, during the period from 1980 to 1989, Chinese government increased the deposit interest rate gradually to raise household savings, and in the meantime decreased loans to enterprises which can reduce excess investment. By the method of adjusting interest rates, Chinese government tried to bring inflation back down. The inflation rate started to go down sharply from 1989Q1 and kept at a relatively low level from 1990Q2-91Q2 (below 3.62%). From 1990 to 1995, the state has repeatedly adjusted interest rates according to the fluctuation of output and inflation. After 1996, inflation was much lower (between -1.97% and 8.31%) and relatively steady. From 1996 to 2003, both the deposit and lending interest rates have been falling for eight consecutive years. In the first two years after financial crisis, both interest rates were relatively low; and from 2012Q3, they have started to fall again and got to a dip from

Fig. 2.5 CPI and inflation.



Note: CPIo is Consumer Price Index from CEIC database. CPIc is calculated Consumer Price Index based on data in CEIC database. CPIu is calculated Consumer Price Index based on data in CEIC and MR databases. PIo_t, PIc_t, and PIu_t are annual inflation in percent annual rates.

2015Q4. The low real lending interest rate is mainly explained by the high inflation, and the high real lending interest rate is mainly explained by the low inflation.

2.4.2 Credit and money

2.4.2.1 Definitions

Credit refers to the ability to borrow. We explore domestic credit (DC) and claims on private sector (CLP), which will be defined by three crucial factors: lenders, borrowers, and financial instruments.

The original database for China's domestic credit and claims on private sector is the PBoC's "All Accounts" financial reporting system. According to the original database, the domestic credit is composed of claims on government (net), claims on non-financial sectors that is named as "claims on private sector (CLP)" in the CEIC database and "domestic credit to private sector" in the World Bank database, and claims on other financial sectors.[4] Domestic credit is supplied by PBoC and banking depository financial institutions. The

[4] Appendix A.3 compares the credit definition of PBoC with those of World Bank.

banking depository financial institutions includes banks, credit cooperatives and finance companies. Credit instruments include loans, debt securities, equities and investment fund shares, etc. The private sector (non-financial sectors) is composed of households and all resident non-financial enterprises. The non-financial resident enterprises refer to those, which mainly engage in the production of market goods and the provision of non-financial market services, and includes public-owned, private-owned, and foreign-controlled non-financial enterprises.[5] Most domestic credit goes to the private sector (non-financial sectors) in China.

Money refers to holdings of cash and deposits and we mainly explore broad money, M2: money plus quasi money. Broad money is the most inclusive method of calculating a given country's money supply. In China's case, broad money, M2, is narrow money M1 plus time, savings, other deposits of resident sectors other than central government and banking institutions and security margin requirement.[6] Money, M1, refers to the most liquid assets, cash, and checkable deposits. Quasi money (near money), describes highly liquid assets which are not cash but can easily be converted into cash, such as bank time deposits and government treasury securities.

2.4.2.2 Description and principal components analysis

Figure 2.6 shows the seasonally adjusted natural log of real credit and money.[7] Figure 2.7 gives the annual growth of real seasonally adjusted series in percent annual rates. Although credit and money are quite distinct concepts, in practice, they move together very closely in China. They show an increasing trend and in most years, they have a positive growth.

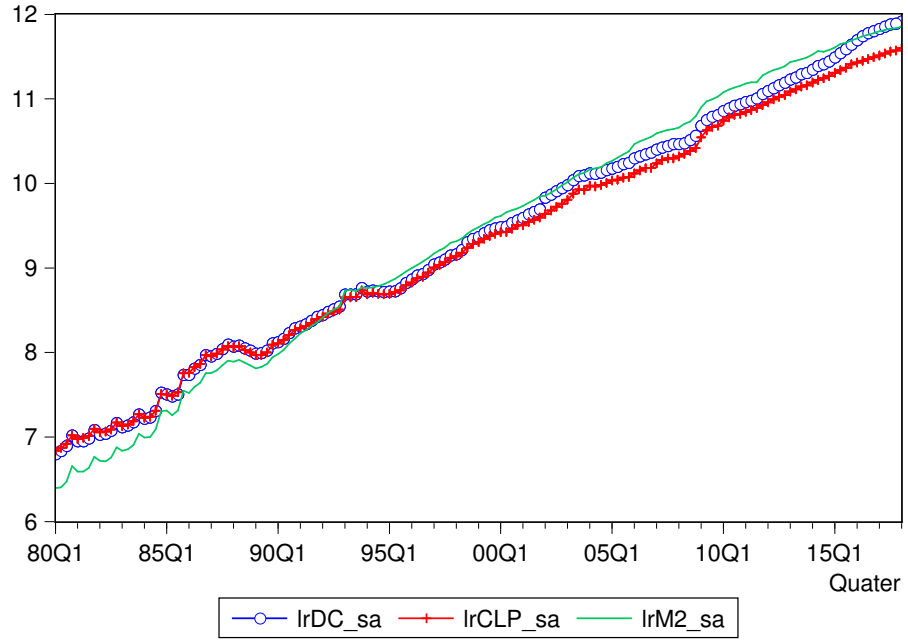
The principal component analysis shows credit and money series are very highly correlated in both levels and growth. All the correlations among the level series of real domestic credit, real claims on private sector, and real broad money are above 0.99, and the first principal component explains almost all of the variation. This is because they share a common trend. In growth rates, the correlation is lower, but still large. The first principal component explains 91% of the variation, and the second principal component 7%.

[5] See National Bureau of Statistics, http://www.stats.gov.cn/tjsj/zbjs/201310/t20131029_44 9553.html.

[6] From June 2001, the coverage of monetary aggregate M2 has been expanded to include the margin account maintained with securities companies (also part of other deposits).

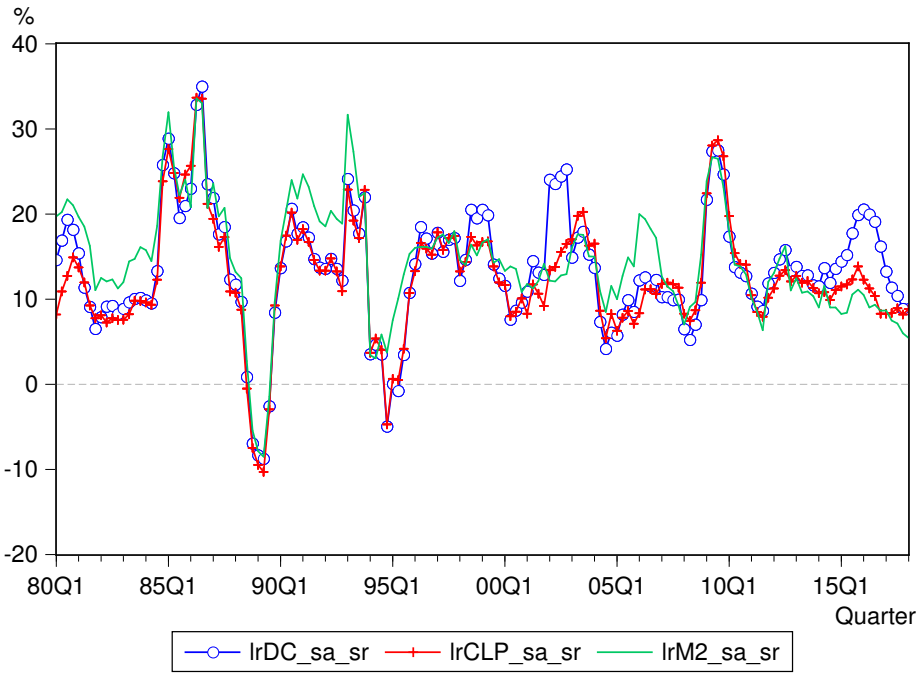
[7] We use STL (Seasonal and Trend decomposition using Loess) decomposition to do seasonal adjustment through this chapter.

Fig. 2.6 lrX_sa_t: seasonal adjusted natural log of real credit and money series.



Note: lrX_sa_t means seasonally adjusted natural log of real X_t series. X_t are nominal M2 (broad money), DC (domestic credit) and CLP (claims on private sector)) series. Get real series, rX_t $(=\frac{X_t}{CPIu_t} * 100)$ first, then get lrX_t by take natural log of rX_t, and then get lrX_sa_t by seasonally adjusting lrX_t series.

Fig. 2.7 $lrX\_sa\_sr_t$: annual real seasonally adjusted credit and money growth in percent annual rates.

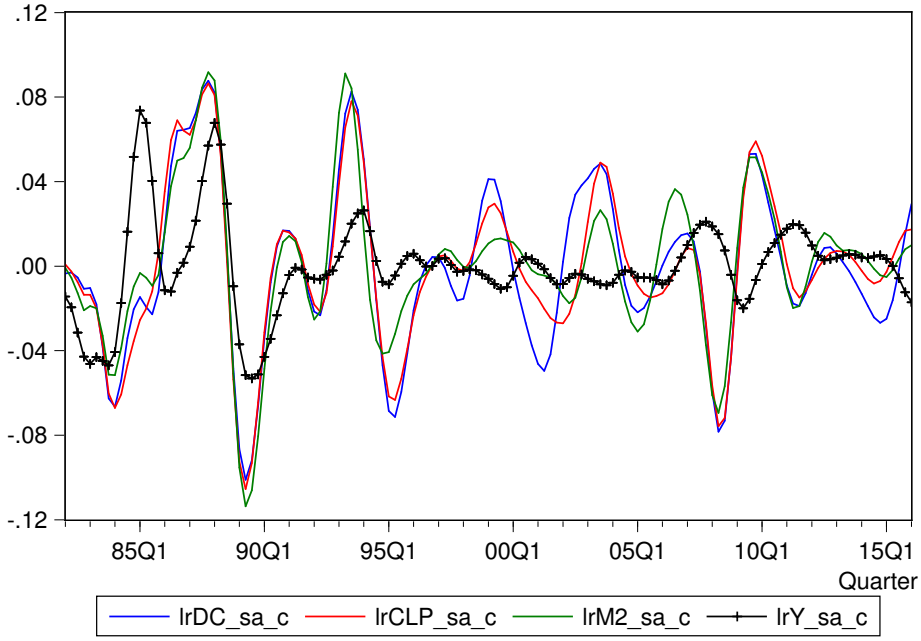


Note: $lrX\_sa\_sr_t$ is annual growth of real seasonally adjusted money series in percent annual rates. That is, $lrX\_sa\_sr_t = (lrX\_sa_t - lrX\_sa_{t-4}) * 100$.

2.4.3 Cycles and identifying the timing of credit booms

We use a Baxter and King (1999) band-pass filter to isolate cyclical fluctuations in seasonally adjusted real money and credit series, alongside a threshold method to identify credit booms.[8] Figure 2.8 shows that seasonally adjusted cycles of real DC, CLP and M2 move together particularly before around 1994 and after 2007, and peak at similar dates such as in 1987, 1993, and 2009. Generally, the apparent co-movement of credit and monetary aggregates indicates that monetary and credit cycles are closely related. We can also observe the amplitude of cycles decreasing towards the end of the sample. This suggests a gradual stabilisation of observed aggregates over time, which is in line with an observable monetary moderation in China over the last two decades, the reduction in inflation and increased stability.

Fig. 2.8 $lrX\_sa\_c_t$: cyclical components of seasonal adjusted natural log of real credit and money series.



Note: we also plot the income cycles, $lrY\_sa\_c_t$. The income shows a decreasing amplitude of cycles towards the end of the sample, which is similar with credit and money.

We identify credit booms explicitly, using a threshold method rather than based on filtered credit cycles, and also employ growth series. We find that if we use Mendoza and Terrones's boom threshold: 1.65 times standard deviation of credit cycle series, and limited threshold:

[8] We do not use nominal series, because they are affected by inflation.

1 standard deviation, few booms can be identified based on the cycle series so that many obvious booms are ignored. If we use 1.65 times standard deviation of credit growth series, and limited threshold: 1 standard deviation, too many booms can be identified based on the growth series so that some busts are included. But if we set the boom threshold as the mean plus standard deviation of cycle or growth series, and limited threshold as the mean, we could find relatively reasonable credit and money boom peaks and durations. Table 2.2 shows credit boom peak dates and duration identified by the boom threshold: mean plus standard deviation of credit cycle or growth series, and limited threshold: mean. The clustered boom peaks of both cycle and growth series, 1986/1987, 1993, and 2009, are identified. Their corresponding boom durations are between 1984-88, 1992-94, and 2009-11.

Table 2.3 shows number of credit and money booms, boom duration, duration fraction spent in upswing and downswing in each period. There are totally 13 booms identified based on the cycle series, and 19 based on the growth series. Looking at both the cycle and growth series, the average boom duration varies between 5-11.3 quarters; the average fraction of the boom duration spent on upswing varies between 0.5-7.8 quarters and spent on downswing varies between 3.2-5.2 quarters. For the booms of cycle series, totally, 2 in 13 have equal downswing and upswing phases; 4 have a longer expansion phase; and 7 have a concentration phase. The booms of growth series shows similar pattern: most booms takes more time to cool. The idea of letting the economy have a "soft" landing in China may contribute to the asymmetry in the length of boom upswing and downswing. When the economy is growing too fast and has serious inflation, Chinese government usually implements a proper tightening policy so that the over-rapid growth of its economy smoothly slows down to an appropriate proportion without large-scale deflation and unemployment.

Summary. Credit and money show clustered boom peaks in 1986/1987, 1993, and 2009. Their corresponding boom durations are between 1984-88, 1992-94, and 2009-11. Many booms take longer time to cool, which may be partly explained by the idea of economy "soft" landing. We discuss the influence of factors such as monetary policies and political events in the following sections.

Table 2.2 China's credit boom peaks and durations.

Peak dates	1	2	3	4	5	6	7	8	9	10	11	12
lrDC_sa_c			87Q4			93Q3		99Q1	03Q2		09Q4	
lrCLP_sa_c			87Q4			93Q3			03Q3		09Q4	
lrM2_sa_c			87Q4			93Q2				06Q3	09Q3	
rDC_sa_sr		85Q1	86Q3			93Q1	93Q4		02Q3		09Q3	
rCLP_sa_sr			86Q2		90Q3	93Q1	93Q4		03Q3		09Q3	
rM2_sa_sr	80Q3	85Q1	86Q2	87Q1	91Q1	93Q1					09Q2	
Peak duration	1	2	3	4	5	6	7	8	9	10	11	12
lrDC_sa_c			86Q1-88Q3			92Q4-94Q4		98Q4-00Q1	02Q1-04Q2		09Q2-10Q4	
lrCLP_sa_c			85Q4-88Q3			92Q4-94Q2			02Q4-04Q3		09Q2-11Q1	
lrM2_sa_c			86Q1-88Q3			92Q3-94Q1				06Q1-07Q2	09Q1-10Q4	
rDC_sa_sr		84Q4-85Q3	85Q3-87Q3			93Q1-93Q3	93Q3-93Q4		02Q1-04Q1		09Q1-10Q2	
rCLP_sa_sr			84Q4-87Q3		90Q1-92Q3	93Q1-93Q3	93Q3-93Q4		02Q1-04Q1		09Q1-10Q4	
rM2_sa_sr	80Q1-81Q3	84Q3-86Q1	86Q1-86Q4	86Q4-87Q4	90Q1-92Q1	92Q1-93Q4					09Q1-10Q4	

Note: The boom threshold is the mean plus standard deviation, and the limited threshold is the mean of credit and money series.

Table 2.3 China's credit boom duration.

		Mean			Median					
			Fraction spent in (Quarter)			Fraction spent in (Quarter)				
Period	No. of booms	Duration	Upswing	Downswing	Duration	Upswing	Downswing	No. of booms (Upswing equal to Downswing)	No. of booms (Upswing longer than Downswing)	No. of booms (Upswing shorter than Downswing)
lrDC_sa_c, lrCLP_sa_c, lrM2_sa_c:										
1980-81	0	0	0	0	0	0	0	0	0	0
1984-88	3	11.3	7.8	3.5	11.0	7.5	3.5	0	3	0
1990-94	3	7.7	3.5	4.2	7.0	3.5	3.5	2	0	1
1998-2000	1	6.0	1.5	4.5	6.0	1.5	4.5	0	0	1
2002-04	2	9.0	4.5	4.5	9.0	4.5	4.5	0	1	1
2006-07	1	6.0	2.5	3.5	6.0	2.5	3.5	0	0	1
2009-11	3	7.7	2.5	5.2	8.0	2.5	5.5	0	0	3
Total	13	47.7	22.3	25.3	47.0	22.0	25.0	2	4	7
rDC_sa_sr, rCLP_sa_sr, rM2_sa_sr:										
1980-81	1	5.0	0.5	4.5	5.0	0.5	4.5	0	0	1
1984-88	6	6.8	3.0	3.8	6.0	2.0	4.0	1	1	4
1990-94	7	5.4	2.2	3.2	3.0	1.5	2.5	1	3	3
1998-2000	0	0	0	0	0	0	0	0	0	0
2002-04	2	9.0	4.5	4.5	9.0	4.5	4.5	1	1	0
2006-07	0	0	0	0	0	0	0	0	0	0
2009-11	3	7.3	2.2	5.2	8.0	2.5	5.5	0	0	3
Total	19	33.6	12.4	21.2	31.0	11.0	21.0	3	5	11

Note: The boom threshold is the mean plus standard deviation, and the limited threshold is the mean of credit and money series.

2.5 Policy and credit

2.5.1 Monetary policy in China

China is a socialist market economy, and monetary authority influences credit and money by monetary policy instruments such as interest rates, reserve requirements, rediscount rates, and open market operations. We have discussed interest rates and financial liberalization, reserve requirement ratios, and credit and money in Section 2.4. This section first gives an overview of related reforms and then discusses different policy measures and their empirical relevance.

2.5.1.1 Interest rate liberalization

Before the December 1978 reforms, the interest rate was completely determined by the central plan, which was consistent with the planned economic system at that time. Even after the reform, the interest rate was controlled for a long period. When the reform started, the easing was mainly limited to the money markets, and it was extremely cautious and had some pressure on the marketization behaviour, and the interest rates had been highly restricted. In the 1970s, developed countries such as European countries and the United States actively

relaxed interest rate control. After the 1980s, with the rise of the wave of global financial liberalization, most countries, including Latin America and other developing countries, also relaxed or completely liberalized the control of interest rates. Since April 1986, interest rates in the United States were completely liberalized. In the case of China, it also gradually relaxed interest rate control and we can roughly divide the liberalization into four stages:[9]

1. **1979-1995, Exploratory stage:** In this period, there is no clear plan and schedule for interest rate liberalization. The PBoC has tried to relax the floating range of interest rates and issuance of national debt and set upper limit for interbank lending. Since January 1986, professional banks can borrow from each other, and the term and interest rate of borrowing and lending can be negotiated and determined between the two banks, starting interest rate liberalization in the interbank lending market. After January 1987, commercial banks can, in accordance with the economic policies of the state, take the benchmark interest rate for working capital loans set by the state and charge up to 20% higher interest. This started the Chinese currency (RMB) loan interest rate liberalization and the 20% limit was gradually raised. In 1991, the issuance of government bonds was underwritten which started the liberalization of bond market interest rates. The 1993 state council document of "the decision on the reform of the financial system" proposed that the long-term goal of China's interest rate reform is to establish a market interest rate management system with the benchmark interest rate of the central bank as the core of regulation and control, and with market capital supply and demand determining various interest rates. In the third 1993 Plenary Session of the 14th Central Committee of the Communist Party of China (CPC), the document "the decision of the CPC central committee on several issues concerning to build the socialist market economy system" proposed that the central bank timely adjusts the benchmark interest rate in accordance with the supply and demand of funds, and it allows the deposit and loan interest rates of commercial banks to float freely within the prescribed range.

2. **1996-2004, Breakthrough stage:** In this period, China has realized the marketization of money market interest rate, bond market interest rate and foreign currency market interest rate. But deposit and lending interest rates were still controlled. Since 1996, China's interest rate liberalization has adhered to the strategy of gradual reform and basically followed the principle of "foreign currency first, then local currency; loans first, then deposits; long term first, then short term; and large amount first, small amount later" in an orderly reform manner. The 2003 report of the 16th National Congress of

[9] See Ren and Xiong (2018), http://www.sohu.com/a/240993312_467568.

the CPC proposed to steadily promote the market-oriented reform of interest rates and optimize the allocation of financial resources. In the third 2003 Plenary Session of the 16th Central Committee of the Communist Party of China (CPC), "the decision of the CPC central committee on several issues concerning the improvement of the socialist market economy system" further clarified that "steadily promote the liberalization of interest rates, establish and improve the formation mechanism of interest rates determined by market supply and demand, and the central bank guides the market interest rates through the use of monetary policy tools. In 2003, the floating range of RMB lending rate was larger, and the lending interest rate of rural credit cooperatives in pilot areas could be 2 times of the benchmark loan interest rate. In 2013, the Postal Savings Bureau and Exchange Office of the state post office have been approved to open postal savings agreement deposits with commercial Banks and rural credit cooperatives, which was the start of deposit interest rate liberalization. In October 2004, the PBoC removed the upper limit on lending rates of commercial Banks, and the upper limit of lending rates of credit cooperatives in both urban and rural areas was extended to 2.3 times of the benchmark interest rate. At same time, it decided to remove the floating low limit on the RMB deposit interest rate and set up a management system of lower limit of deposit interest rate.

3. **2005-2011, Slow stage:** The interest rate liberalization in this period was slow because of financial crisis shocks and decreasing economic growth.

4. **2012-2015, Full interest rate liberalization:** In 2012-13, restrictions on the lending rate were fully relaxed allowing it to be determined by the market. From 2015, restrictions on the deposit rate were also relaxed. The PBoC announced that from 8 June 2012, the upper limit of the floating range of deposit interest rates of financial institutions will be adjusted to 1.1 times of the benchmark interest rate, and the lower limit of the floating range of lending interest rate of financial institutions will be adjusted to 0.8 times of the benchmark interest rate. From 6 July 2012, the PBoC has lowered the benchmark interest rate of RMB deposits and loans for financial institutions, and adjusted the lower limit of the floating range of the interest rate of RMB loans for financial institutions to 0.7 times of the benchmark interest rate. On July 19, 2013, the PBoC has decided to fully relax the control on the loan interest rate of financial institutions from July 20 by removing the lower limit of 0.7 times of the benchmark interest rate and allowing financial institutions to independently determine the lending interest rate in accordance with commercial principles. In 2015, the PBoC adjusted the upper limit of the floating range of deposit interest rate to 1.2 times the

benchmark interest rate; and also in 2015, the commercial banks, rural cooperative financial institutions etc. were no longer subject to a ceiling on the floating deposit interest rate.

2.5.2 Policy measures

We employ four policy measures: Two monetary policy measures, one capturing window guidance policy alongside an index capturing the overall monetary policy stance, and two indicator variables, capturing political conferences that may have had an impact on credit markets.

2.5.2.1 Window guidance

China's monetary policy has always been predominantly quantitative in nature, and the use of quantitative tools has long been the norm in implementing China's monetary policy. But the PBoC embraced a gradual switch from quantity-based measures to guide monetary policy toward a price-based approach that gave more weight to interest rates and let liquidity levels be determined by the price, rather than volume, of capital (Chen et al., 2017). Since 1998 when the PBoC abolished its pure quantity-based credit plan, a direct control on the credit quantity of state-owned banks, the PBoC has relied on lending quotas known as "window guidance" to influence bank behaviour and thereby affect monetary aggregates. Window guidance refers to a mild, non-mandatory monetary policy tool that the central bank advises banks to adjust the amount and pace of credit supply until a credit growth target is met. It is also used to optimize the credit structure by moderating banks' allocation of credit to sectors and regions in line with policy objectives. As a monetary policy tool, window guidance, is not required by law but only advisory guidance. However, such advise from the PBoC is to a large extent quasi-mandatory in practice. If private financial institutions do not follow the guidance, although they do not bear legal responsibility, they may eventually bear other aspects of economic sanctions. Chen et al. (2017) classified the PBoC's window guidance policy into five stances and employed dummy variable approach to get a dummy, DWG_t, which reflects monetary policy stance. They summarized the episode-by-episode development of the PBoC's window guidance policy stances from 1998Q1-2017Q1 to Table 1 in their paper and we put this table in the following (Table 2.4):

Table 2.4 China window guidance policy stances.

Indicator (DWG_t)	**Stance**	**Period**	**Definition**
-2	Strongly discouraging	2003Q1 - 04Q4 2006Q2 - 08Q2 2009Q2 - 10Q1	QMPR explicitly discourages growth of total credit.
-1	Weakly discouraging	2005Q1 - 06Q1 2010Q1 - 12Q2	QMPR states the target of optimizing credit structure, provides risk alerts and/ or mentions that banks should manage the pace of credit growth.
0	No explicit directions	2001Q1 - 02Q4 2012Q3 - 14Q2	QMPR only states the target of optimizing credit structure and separately listing the sectors that should be both discouraging and encouraging (differentiated approach to credit guidance) or no explicit direction of credit growth.
1	Weakly encouraging	2014Q3 - 17Q1	QMPR only lists sectors that to be encouraged for the target of optimizing credit structure.
2	Strongly encouraging	1998Q1 - 2000Q4	QMPR encourages the growth of total credit explicitly.

Note: QMPR stands for PBoC's Quarterly Monetary Policy Report.

2.5.2.2 Monetary policy stance

To cover the whole period, 1979Q1-18Q3, we classified the PBoC's monetary policy into seven stances in a monetary policy stance index, DMP_t, according to the central bank's Quarterly Monetary Policy Report (QMPR), websites information and our judgment. This gives us Table 2.5.

Table 2.5 China monetary policy stances.

Indicator (DMP_t)	**Stance**	**Period**
-3	tight monetary policy	1985Q1 - 86Q2 1987Q1 - 87Q4 1988Q4 - 89Q4
-2	moderately tight monetary policy	1988Q1 - 88Q3 1993Q1 - 95Q4
-1	prudent and moderately tight monetary policy	2003Q3 - 07Q3 2011Q1 - 11Q4
0	prudent and neutral monetary policy	2017Q1 - 18Q4
1	prudent and moderately loose monetary policy	1986Q3 - 86Q4 1998Q1 - 2003Q2
2	moderately loose monetary policy	1990Q1 - 90Q4 1991Q1 - 91Q4
3	loose monetary policy	1979Q1 - 84Q4 1992Q2

Although the PBoC let markets determine the lending rate since 2013 and the deposit rate since 2015, there are various tools to control credit quantity directly or indirectly. For example, the PBoC adopts a Macro Prudential Assessment (MPA) system in 2016 to evaluate whether banks meet the requirement of the PBoC's credit policy on small and micro enterprises (SMEs), agriculture-related sectors, regional credit, as well as the use of the central bank's structural funds (such as agriculture-related re-loans). In addition, the China Banking Regulatory Commission (CBRC) often set credit goals for banks and evaluate whether banks achieve these goals. These goals are generally put forward by the state council, which are essentially political tasks. There are goals to encourage credit, for example, the CBRC set goals on bank's loan to SMEs in 2015: the growth of loans to SMEs should not be lower than the average growth rate of various loans, the number of SMEs applying loans should not be lower than the number in the same period of previous year, and the loan acquisition rate of SMEs should not be lower than that in the same period of previous year. There are also goals to restrict loans, for example, the PBoC adopts different housing credit policy for different types of residents in different cities and imposes credit restrictions for local government financing platforms and companies with special purpose.

2.5.3 Credit, money, and conferences

We try to explore the relations between credit, money and important conferences in China, which gives an indication for policy shifts. The important conferences are the Chinese Communist Party National Representatives Congress (CCPNRC), and the Two Sessions which refers to the National People's Congress (NPC) and the Chinese People's Political Consultative Conference (CPPCC). Chinese Communist Party National Representatives Congress is a party congress that is held every five years. The dates are given in Table 2.6. In the past two decades the CCPNRC has been pivotal at least as a symbolic part of leadership changes. The National People's Congress is the national legislature of the People's Republic of China. Under China's constitution, the NPC is structured as a unicameral legislature, with the power to legislate, the power to oversee the operations of the government, and the power to elect the major officers of state. The NPC is elected for a term of five years. It holds annual sessions every spring, usually lasting from 10 to 14 days, in the Great Hall of the People on the west side of Tiananmen Square in Beijing. The NPC's sessions are usually timed to occur with the meetings of the National Committee of the People's Political Consultative Conference, a consultative body whose members represent various social groups. As the big NPC and the CPPCC every five years are the main deliberative bodies of China, they are often referred to as the Lianghui (Two Sessions). We will examine the links between

credit and money and the conferences using two dummies (1 for conference), for CCPNRC, $DCCPNRC_t$, and Two Sessions, DTS_t.

Table 2.6 China conference dates.

Indicator	CCPNRC	Two Sessions
1	1977Q3	1978Q1
1	1982Q3	1983Q2
1	1987Q4	1988Q1
1	1992Q4	1988Q2
1	1997Q3	1993Q1
1	2002Q4	1998Q1
1	2007Q4	2003Q1
1	2012Q4	2008Q1
1	2017Q4	2013Q1
1		2018Q1
0	other quarters over 1977Q1-18Q3	other quarters over 1977Q1-18Q3

2.5.4 Empirical relationship between policy and credit

This section documents empirical relationships of credit and monetary aggregates with policy measures. Sometimes we use the term, monetary policy, to cover both respective policy measures. We obtain qualitative evidence, based on descriptive statistics of the data and then investigate correlations between variables. Then we give further quantitative evidence based on regressions of credit and monetary aggregates on policy measures.

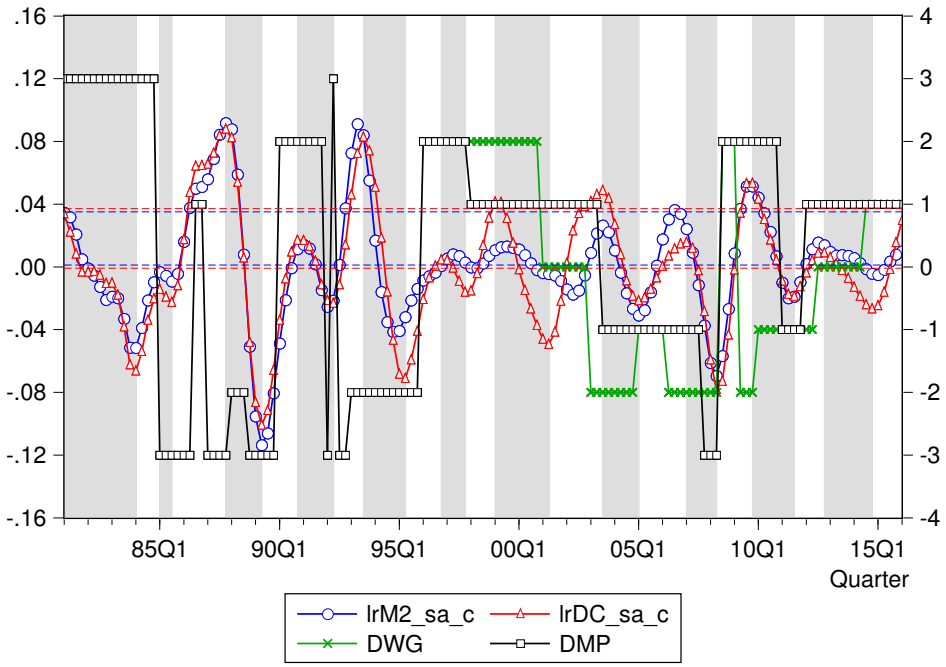
2.5.4.1 Credit, money and monetary policies

Figure 2.9 graphs four series: seasonally adjusted credit cycle series ($lrDC\_sa\_c_t$; left axis), seasonally adjusted money cycle series ($lrM2\_sa\_c_t$; left axis), a window guidance dummy (DWG_t; right axis), and a monetary policy index (DMP_t; right axis). Plotting these series in the same figure allows to evaluate how these two policy instruments affect the credit and money cycles. Horizontal lines in the figure give the boom threshold, mean plus standard deviation, as well as the limited threshold, mean, for the corresponding credit and money cycle series. The shaded area roughly corresponds to phases of cyclical credit contractions. Using similar plots, Figure 2.10 shows credit and money growth alongside window guidance and overall monetary policy stance.

In Figure 2.9, we find that some cycles are in the expansion phase when the monetary policy is loose and the Quarterly Monetary Policy Report encourages growth of credit, for example, from 1998Q1-99Q1. There are also some cycles in the downswing phase when monetary policy is loose and the Quarterly Monetary Policy Report encourages growth of credit, for example, from 1999Q2-2000Q4. So the upswing phase of credit and money

cycles does not necessarily correspond to loose monetary policies and window guidance, and the downswing phase does necessarily correspond to tight monetary policies and window guidance. However, there does appear to be a closer relationship between policy instruments and cyclical movements in credit and money aggregates towards the end of the sample. This might suggest that monetary policy gained a greater effect on cycles, which may have had a stabilizing impact. Figure 2.10 again shows there seems to appear a clearer relationship towards the end of the sample, whereas policy instruments and growth of credit and money appear rather disconnected over the first 15 years.

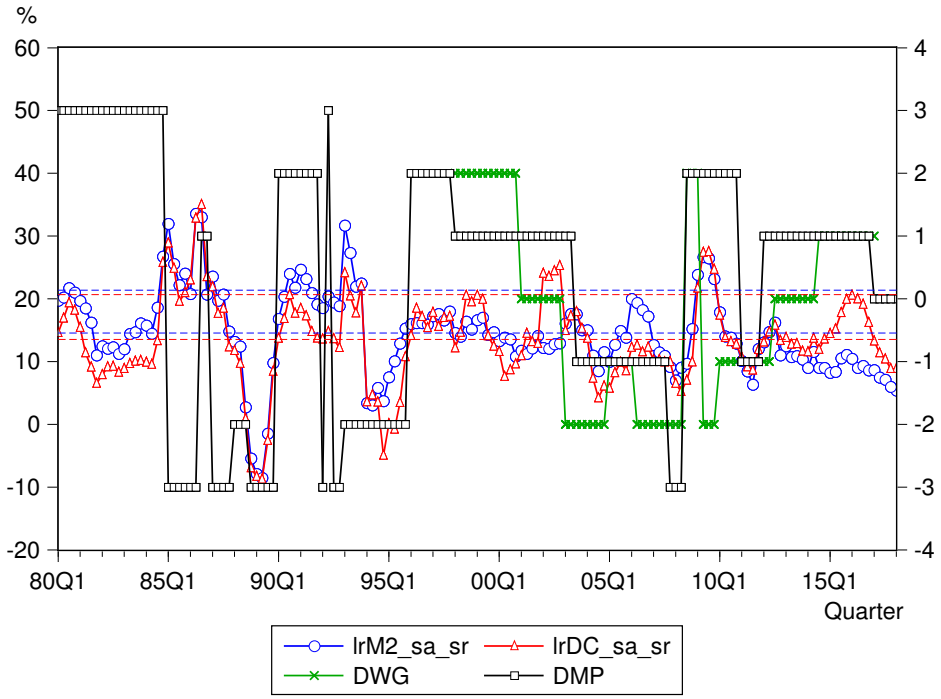
Fig. 2.9 Credit and money cycles and window guidance dummy and monetary policy index.



Note: The left axis is for seasonally adjusted cycle series, $lrDC\_sa\_c_t$ and $lrM2\_sa\_c_t$, and the right axis is for window guidance dummy, DWG_t and monetary policy index, DMP_t. The above horizontal blue dash line is the boom threshold: mean plus standard deviation of $lrDC\_sa\_c_t$, and the bottom horizontal blue dash line is the limited threshold: mean. The above horizontal red dash line is the boom threshold: mean plus standard deviation of $lrM2\_sa\_c_t$, and the bottom horizontal red dash line is the limited threshold: mean. The shaded area roughly corresponds to the downswing phase of $lrDC\_sa\_c_t$.

The correlation coefficients shown in Table 2.7, quantify the relationship between window guidance, DWG_t, and credit and monetary aggregates. We not only calculate the contemporaneous correlation coefficients, but also correlations for up to four leads and lags. Leads allow to evaluate policy reactions to considered monetary and credit aggregates whilst lags

Fig. 2.10 Growth of credit and money and window guidance dummy and monetary policy index.



Note: The left axis is for seasonally adjusted growth series, $rDC\_sa\_sr_t$ and $rM2\_sa\_sr_t$, and the right axis is for window guidance dummy, DWG_t and monetary policy index, DMP_t. The above horizontal blue dash line is the boom threshold: mean plus standard deviation of $rDC\_sa\_sr_t$, and the bottom horizontal blue dash line is the limited threshold: mean. The above horizontal red dash line is the boom threshold: mean plus standard deviation of $rM2\_sa\_sr_t$, and the bottom horizontal red dash line is the limited threshold: mean.

give policy effects. 22 out of 48 correlation coefficients are significant at the 10% level. Real credit and monetary cycles, $lrCLP\_sa\_c_t$ and $lrM2\_sa\_c_t$, have significant positive correlations (0.22 to 0.34) with the 2-4 lags of window guidance, DWG_{t-2}, DWG_{t-3} and DWG_{t-4}. The real credit growth, $lrDC\_sa\_sr_t$ and $lrCLP\_sa\_sr_t$, is significantly correlated (0.22 to 0.47) with 1-4 lags with window guidance. The real credit and money cycle series show significant negative correlations (-0.31 to -0.21) with 1-3 leads of window guidance. M2 growth shows negative correlations (-0.32 to -0.26) with 1-4 leads of window guidance. This suggests that there is a relationship between credit and monetary aggregates and window guidance. Correlations are significantly positive with lags of window guidance and significantly negative in leads. Hence window guidance tends to positively affects credit and monetary aggregates, whilst policy reaction to money and credit tend to be counter-cyclical. Contemporary correlations between credit and money and window guidance is insignificant.

This implies that, whilst there is both a significant policy reaction and effect, this relationship is lagged.

We further explore the relationships between monetary policy stance, DMP_t, credit, and money (see Table 2.8). 25 of 48 correlation coefficients are significant at 10% level. The real credit and money cycles show negative significant correlations (-0.38 to -0.17) with the leads of monetary policies, but no significant correlations with lags. The growth of credit and money shows significant positive correlations with contemporary and future monetary policy and negative correlations with the 4th lag quater of monetary policy. Findings for cyclical variables are hence similar to those for growth series, albeit less significant in lags.[10]

Table 2.7 Correlation coefficients between credit and money and window guidance dummy, DWG_t.

	Y: DWG	Y: DWG	Y: DWG	Y: DWG	Y: DWG	Y: DWG	Y: DWG	Y: DWG	Y: DWG
Correlations	(Xt, Yt)	(Xt, Yt-1)	(Xt, Yt-2)	(Xt, Yt-3)	(Xt, Yt-3)	(Xt, Yt+1)	(Xt, Yt+2)	(Xt, Yt+3)	(Xt, Yt+4)
X: lrDC_sa_c	-0.18	-0.03	0.10	0.18	0.19	-0.29**	-0.31***	-0.25**	-0.14
X: lrCLP_sa_c	-0.14	0.00	0.15	0.25**	0.28**	-0.22*	-0.21*	-0.11	0.03
X: lrM2_sa_c	-0.10	0.07	0.22*	0.32***	0.34***	-0.22*	-0.26**	-0.20	-0.08
X: lrDC_sa_sr	0.17	0.31***	0.45***	0.47***	0.39***	0.04	0.01	0.02	0.02
X: lrCLP_sa_sr	-0.09	0.06	0.22*	0.26**	0.19	-0.18	-0.17	-0.11	-0.04
X: lrM2_sa_sr	-0.15	0.01	0.14	0.15	0.09	-0.26**	-0.32***	-0.30***	-0.27**

Note: * denots significance at the 10% level. ** denots significance at the 5% level. *** denots significance at the 1% level.

Summary. Both the plots and correlations tend to tell the same story. Loose monetary policy and window guidance tend to have a positive effect on credit and money while policy responds negatively to past credit and money. Window guidance tends to show this for both cycles and growth. The correlation in the same period is more mixed, some negative and some positive. Although there are few exceptions, this pattern over time is generally consistent with monetary policies designed to stabilize credit and money growth.

2.5.4.2 Credit, money and political conferences

Figure 2.11 shows the relations of conference dates with domestic credit cycles and growth. the left axis is for cycle series, and the right axis is for growth series. We plot the credit boom threshold: mean plus standard deviation of credit series, and the limited threshold: mean. The vertical solid line corresponds to the CCPNRC's date, and the vertical dashed line corresponds to the Two Sessions date. The shaded area starts from a year before the CCPNRC and ends in a year after the Two Sessions. This figure shows that the boom threshold identifies

[10] An exception is that the domestic credit growth shows a positive significant correlation the 1st lead quarter of monetary policy.

Table 2.8 Correlation coefficients between credit and money and monetary policy index, DMP_t.

	Y: DMP	Y: DMP	Y: DMP	Y: DMP	Y: DMP	Y: DMP	Y: DMP	Y: DMP	Y: DMP
Correlations	(Xt, Yt)	(Xt, Yt-1)	(Xt, Yt-2)	(Xt, Yt-3)	(Xt, Yt-4)	(Xt, Yt+1)	(Xt, Yt+2)	(Xt, Yt+3)	(Xt, Yt+4)
X: lrDC_sa_c	-0.01	0.01	0.00	-0.03	-0.06	-0.09	-0.19**	-0.30***	-0.38***
X: lrCLP_sa_c	-0.01	0.01	0.00	-0.03	-0.05	-0.08	-0.17**	-0.27***	-0.35***
X: lrM2_sa_c	0.00	0.03	0.02	0.00	-0.02	-0.07	-0.17**	-0.28***	-0.36***
X: lrDC_sa_sr	0.22***	0.23***	0.22***	0.21**	0.15*	0.16**	0.06	-0.06	-0.17**
X: lrCLP_sa_sr	0.17**	0.18**	0.16**	0.16**	0.11	0.12	0.03	-0.08	-0.19**
X: lrM2_sa_sr	0.15*	0.16*	0.14*	0.13	0.08	0.11	-0.01	-0.12	-0.23***

Note: * denots significance at the 10% level. ** denots significance at the 5% level. *** denots significance at the 1% level.

5 quarterly credit cycle boom peaks, and 1 of them happen in the CCPNRC quarter (1987Q4), and the other 3 of these peaks happen within a year after the Two Sessions. The boom threshold identifies 6 credit quarterly growth boom peaks, 2 of them happen in the conference quarters (1993Q1 and 2002Q4), and the peak in 1993Q4 happens within a year after the Two Sessions. So most of domestic credit booms peaks happen in a conference year or within a year after the Two Sessions.

Table 2.9 shows the correlations between dates of the Two Sessions, DTS_t, and credit and money. The correlation between the dates of conferences and credit and money are generally weak and 42 of 48 coefficients are insignificant at 10% significance level. There are few exceptions including: the cycle series of money and the growth series of credit and money show negative correlations with the 4th lag quarter of the Two Sessions. This implies that money and credit tend to decrease after around a year of the Two Sessions. We do not find any significant correlation of the date of the Communist Party National Representatives Congress with credit and money.

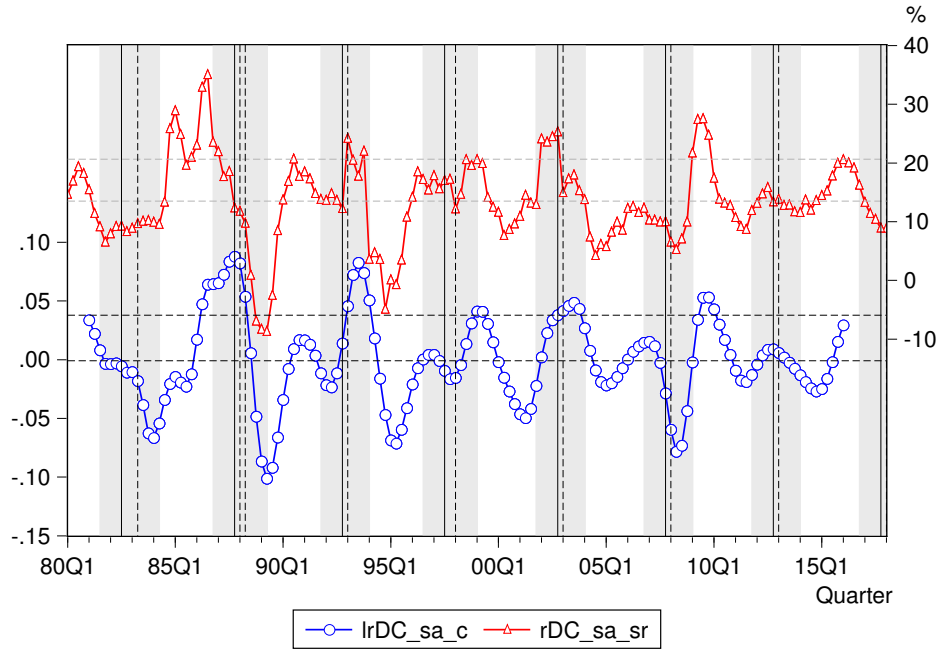
Table 2.9 Correlation coefficients between credit and money and the Two Sessions, DTS_t.

	Y: DTS	Y: DTS	Y: DTS	Y: DTS	Y: DTS	Y: DTS	Y: DTS	Y: DTS	Y: DTS
Correlations	(Xt, Yt)	(Xt, Yt-1)	(Xt, Yt-2)	(Xt, Yt-3)	(Xt, Yt-4)	(Xt, Yt+1)	(Xt, Yt+2)	(Xt, Yt+3)	(Xt, Yt+4)
X: lrDC_sa_c	0.12	0.05	-0.02	-0.08	-0.10	0.15	0.15	0.14	0.11
X: lrCLP_sa_c	0.10	0.05	-0.03	-0.10	-0.13	0.12	0.11	0.09	0.08
X: lrM2_sa_c	0.13	0.07	-0.03	-0.12	-0.18**	0.14	0.13	0.11	0.09
X: lrDC_sa_sr	-0.04	-0.07	-0.11	-0.14*	-0.19**	-0.01	0.03	0.06	0.07
X: lrCLP_sa_sr	-0.01	-0.04	-0.10	-0.12	-0.18**	-0.03	0.01	0.02	0.02
X: lrM2_sa_sr	-0.01	-0.03	-0.11	-0.15*	-0.21**	-0.06	0.00	0.02	0.03

Note: * denots significance at the 10% level. ** denots significance at the 5% level. *** denots significance at the 1% level.

Even though not all credit and money series show significant correlations with the Two Sessions, we can find hints that credit and money tend to increase before the Two Sessions

Fig. 2.11 Real domestic credit cycles and growth and conferences.



Note: $lrDC\_sa\_c_t$ is cycle series of seasonally adjusted natural log of real domestic credit, and $rDC\_sa\_sr_t$ is growth rate (%) of seasonally adjusted natural log of real domestic credit. The left axis is for $lrDC\_sa\_c_t$, and the right axis is for $rDC\_sa\_sr_t$. The above horizontal grey dash line is the boom threshold: mean plus standard deviation of $lrDC\_sa\_c_t$, and the bottom horizontal grey dash line is the limited threshold: mean. The above horizontal black dash line is the boom threshold: mean plus standard deviation of $rDC\_sa\_sr_t$, and the bottom horizontal black dash line is the limited threshold: mean. The vertical solid line corresponds to the CCPNRC quarter, and the vertical solid line corresponds to the Two Sessions quarter. The shaded area starts from a year before CCPNRC and ends a year after Two Sessions.

and decrease after. Since credit drives economic growth and criteria such as performance in GDP are key factors in the promotion of Chinese officials, there is an incentive to boost credit before conferences. The National People's Congress has the power to oversee the operations of the government and to select main administrators of states. So officials tend to increase credit for economic growth when the Two Sessions are approaching. But after the Two Sessions, incentives for officials' promotion temporarily fall. This may partly explain the correlations between credit and the Two Sessions.

Summary. Most credit booms peaks of credit and money happen in a conference year or within a year after the Two Sessions. Credit and money tend to increase when the Two

Sessions are approaching and decrease after, which may partly be explained by officials' incentives of promotion.

2.5.4.3 Quantitative evidence

The plots and correlation coefficient analysis in above sections give qualitative evidence and indicate some association between credit and money and policy measures. We attempted to further quantify this association using simple linear regressions of filtered cycles and growth of credit and money on considered policy measures. Policy measures enter regressions separately, to allow a comparison of their respective contribution to explained variations in dependent variables.

Table 2.10 gives results for regressions of credit and monetary aggregates on policy measures. Generally there is little explanatory power of policy on cyclical variables and some explanatory power (10-20%) for significant (lagged) effects of the window guidance measure on credit growth. The effect is positive, which is in line with previous correlations on policy effects. There are some further significant effects of policy on growth series, which are large for the two-sessions indicator, but generally carry close to no explained variation. Intercepts have the largest effect on growth regressions, suggesting that whilst in some instances policy has significant impacts, most of Chinese credit and monetary expansion is driven by other factors. Table 2.11 considers policy (window guidance and monetary policy stance) reactions to credit and monetary aggregates. Policy reactions are overall negative in almost all cases, which gives evidence for counter-cyclical policy. There are large significant effects for almost all cases considered that differ mainly in lags and persistence. Explained variations are mostly higher than in previous regressions but yet remain relatively low. Intercepts are low and largely insignificant, which indicates that there are comparatively small autonomous policy reactions. So while there is some qualitative indication of an association, the fit of these regressions is quite low and there are possible issues of endogeneity, so we do not put much weight on these results.

This chapter studies the effect of policy measures on credit and money in isolation. We extend this analysis in Chapter 4, Macroeconomic Interactions of Money in China, studying the effect of other factors such as income and interest rates on credit growth.

2.6 Conclusion

This chapter considers the impact of policy and big political events on credit cycles in China, in particular investigating to which extent credit and monetary cycles are policy-driven. Following a discussion of measurement and methodologies underlying common trend-cycle

decompositions, threshold method, and econometric modelling, we review crucial monetary policy reforms. We explore domestic credit (DC) and claims on private sector (CLP), as well as broad money (M2). Although credit and money are quite distinct concepts, in practice, they move together very closely in China over 1979Q1-2018Q1. Whether these variables are in real level or real growth the principal components analysis shows that they are very highly correlated.

We extract cyclical components from the data using a Baxter and King band-pass filter. In China's case, if we set the credit boom thresholds as a proportion such as 1.65 suggested by Mendoza and Terrones (2008) of the standard deviation of credit cycles, only few extreme credit booms are identified. We therefore apply an alternative threshold method, where we set the boom threshold as mean plus standard deviation and the limited threshold as the mean of credit cycle series (or growth). This allows us to correctly identify most booms. Both the cycle and growth of credit and money variables show clustered boom peaks in 1986/1987, 1993 and 2009. Most booms have longer downswing than upswing phase, which may be partly explained by the state's idea of a "soft" landing of the economy.

We then consider relations of credit and money with policies, using descriptive statistics, correlations, and regression analysis. The qualitative evidence suggests that loose monetary policy and window guidance tend to increase credit and money. Policy tends to respond negatively to past credit and money: monetary policy tends to be loose and window guidance tends to encourage credit growth after a concentration of credit and money. The correlation in the same period is more mixed, some negative and some positive. Although there are few exceptions, this pattern over time is generally consistent with monetary policy designed to stabilize credit and money growth. We further find that most of credit and money booms peak in conference years or within a year after the Two Sessions. Credit and money go up before the Two Sessions and go down after. We can generally not confirm these results quantitatively: Regression analysis indicates relatively low explained variation of the data, with rare significant policy effects, except for significant effects of the Two Sessions on credit and monetary growth. There is some evidence for a negative effect of credit and money on policy, that suggests a counter-cyclical window guidance and monetary policy stance.

Our analysis offers some insights into the dynamics and determinants of credit in China. From an econometric perspective, we show that the Baxter and King band-pass filter, alongside our threshold method, are reasonable tools to filter credit cycles and identify credit booms. We further provide evidence for the effectiveness of monetary stabilisation policies in China. Our findings have implications for the identification of credit cycles and booms in China and therefore the design and conduct of macroprudential policy, such as the activation

and deactivation of monetary policy tools. Furthermore, the relation between credit and money and the Two Sessions implies that the effects of politics on market mechanism.

In this chapter, the regression analysis suggests that credit and monetary expansion is also driven by other factors. This chapter has also discussed the impact of other financial and macroeconomic variables on credit cycles descriptively, indicating strong correlations. Further investigation of the interaction of these variables necessitates a multivariate framework, which we approach in Chapter 3 and 4.

Table 2.10 Effects of monetary policies and conferences on credit and money.

Effects of DWG_t and DMP_t					Effects of conferences				
Indep.\Dep.	$lrM2\_sa\_c_t$	$lrDC\_sa\_c_t$	$lrM2\_sa\_sr_t$	$lrDC\_sa\_sr_t$	**Indep.\Dep.**	$lrM2\_sa\_c_t$	$lrDC\_sa\_c_t$	$lrM2\_sa\_sr_t$	$lrDC\_sa\_sr_t$
C	0.002	-0.001	13.112***	14.132***	C	0.001	-0.002	14.631***	13.526***
DWG_t	-0.001	-0.003	-0.424	0.604	$DCCPNRC_t$	0.013	0.017	-1.919	-0.008
R^2	0.009	0.031	0.023	0.028	R^2	0.007	0.009	0.004	0.000
C	0.002	0.000	13.094***	14.213***	C	0.001	-0.002	14.539***	13.545***
DWG_{t-1}	0.001	-0.001	-0.014	1.103***	$DCCPNRC_{t-1}$	0.014	0.014	-0.156	-0.377
R^2	0.004	0.001	0.000	0.093	R^2	0.007	0.007	0.000	0.000
C	0.003	0.001	13.063***	14.243***	C	0.001	-0.001	14.517***	13.582***
DWG_{t-2}	0.003*	0.002	0.305	1.573***	$DCCPNRC_{t-2}$	0.012	0.011	0.301	-1.248
R^2	0.049	0.010	0.011	0.187	R^2	0.006	0.004	0.000	0.001
C	0.004	0.001	12.923***	14.093***	C	0.001	-0.001	14.602***	13.622***
DWG_{t-3}	0.005***	0.004	0.279	1.578***	$DCCPNRC_{t-3}$	0.006	0.007	-1.568	-2.109
R^2	0.103	0.032	0.009	0.190	R^2	0.001	0.001	0.002	0.004
C	0.004	0.001	12.756***	13.894***	C	0.001	-0.001	14.620***	13.610***
DWG_{t-4}	0.005***	0.004	0.054	1.243***	$DCCPNRC_{t-4}$	-0.005	0.000	-1.947	-1.847
R^2	0.119	0.038	0.000	0.118	R^2	0.001	0.000	0.004	0.003
C	0.001	-0.001	14.350***	13.278***	C	0.000	-0.002	14.555***	13.597***
DMP_t	0.000	0.000	0.615**	0.841***	DTS_t	0.019	0.019	-0.414	-1.220
R^2	0.000	0.000	0.032	0.054	R^2	0.017	0.013	0.000	0.002
C	0.001	-0.001	14.324***	13.251***	C	0.001	-0.001	14.583***	13.645***
DMP_{t-1}	0.001	0.000	0.660**	0.873***	DTS_{t-1}	0.010	0.009	-1.003	-2.288
R^2	0.001	0.000	0.037	0.059	R^2	0.004	0.003	0.001	0.005
C	0.001	-0.001	14.326***	13.253***	C	0.002	-0.001	14.713***	13.720***
DMP_{t-2}	0.001	0.000	0.613**	0.816***	DTS_{t-2}	-0.005	-0.004	-3.479	-3.718
R^2	0.001	0.000	0.032	0.052	R^2	0.001	0.001	0.013	0.014
C	0.001	-0.001	14.332***	13.264***	C	0.002	0.000	14.776***	13.769***
DMP_{t-3}	0.000	0.000	0.562**	0.739***	DTS_{t-3}	-0.019	-0.013	-4.698*	-4.665*
R^2	0.000	0.000	0.027	0.043	R^2	0.016	0.006	0.024	0.021
C	0.001	-0.001	14.383***	13.334***	C	0.003	0.000	14.877***	13.834***
DMP_{t-4}	0.000	-0.001	0.397	0.513*	DTS_{t-4}	-0.027**	-0.017	-6.631***	-5.912**
R^2	0.000	0.002	0.014	0.021	R^2	0.033	0.011	0.047	0.034

Note: This table gives estimates based on the following regressions:

$$lrX\_sa\_c_t = \alpha + \beta D_{t-i} + \mu, \tag{2.5.1}$$

$$lrX\_sa\_sr_t = \alpha + \beta D_{t-i} + \mu, \tag{2.5.2}$$

where $i = 1,2,3,4$, α is a constant, β gives coefficients. $lrX\_sa\_c_t$ is the dependent variable in model (2.5.1): cycle series of seasonally adjusted real doemstic credit ($lrDC\_sa\_c_t$) or broad money (($lrM2\_sa\_c_t$)). $lrX\_sa\_sr_t$ is the dependent variable in model (2.5.2): growth series of seasonally adjusted real doemstic credit ($lrDC\_sa\_sr_t$) or money (($lrM2\_sa\_sr_t$)). The independent variable, D_t, is a monetary policy variable, DWG_t or DMP_t, or a conference dummy, $DCCPNRC_t$ or DTS_t. Policy measures are included indivdually to allow comparison of respective explanatory power. We estimated further models including all variables and lags jointly that give explained variations ranging between 70 and 80% but leave other results largely unchanged. Significance levels: *10%, ** 5% , *** 1%.

Table 2.11 Effects of credit and money on monetary policies.

Effects of cycle series			Effects of growth series		
Indep.\Dep.	DWG_t	DMP_t	**Indep.\Dep.**	DWG_t	DMP_t
C	-0.234	0.212	C	0.528	-0.451
$lrM2\_sa\_c_t$	-6.289	0.285	$lrM2\_sa\_sr_t$	-0.054	0.051**
R^2	0.009	0.000	R^2	0.023	0.032
C	-0.202	0.203	C	0.912	-0.302
$lrM2\_sa\_c_{t-1}$	-13.640*	-3.759	$lrM2\_sa\_sr_{t-1}$	-0.082**	0.040*
R^2	0.043	0.004	R^2	0.053	0.019
C	-0.181	0.196	C	1.101*	0.142
$lrM2\_sa\_c_{t-2}$	-15.182**	-9.586**	$lrM2\_sa\_sr_{t-2}$	-0.096**	0.008
R^2	0.053	0.029	R^2	0.071	0.001
C	-0.173	0.189	C	0.912	0.591
$lrM2\_sa\_c_{t-3}$	-10.859	-15.482***	$lrM2\_sa\_sr_{t-3}$	-0.081**	-0.024
R^2	0.027	0.076	R^2	0.051	0.007
C	-0.174	0.173	C	0.640	1.018***
$lrM2\_sa\_c_{t-4}$	-3.266	-19.960***	$lrM2\_sa\_sr_{t-4}$	-0.060	-0.054**
R^2	0.002	0.128	R^2	0.028	0.035
C	-0.245	0.212	C	-0.827*	-0.580*
$lrDC\_sa\_c_t$	-8.857	-0.543	$lrDC\_sa\_sr_t$	0.046	0.065***
R^2	0.031	0.000	R^2	0.028	0.054
C	-0.230	0.195	C	-0.390	-0.389
$lrDC\_sa\_c_{t-1}$	-14.010**	-4.402	$lrDC\_sa\_sr_{t-1}$	0.015	0.049**
R^2	0.077	0.007	R^2	0.003	0.032
C	-0.216	0.176	C	-0.297	-0.032
$lrDC\_sa\_c_{t-2}$	-15.019***	-9.875**	$lrDC\_sa\_sr_{t-2}$	0.008	0.021
R^2	0.088	0.036	R^2	0.001	0.006
C	-0.199	0.158	C	-0.358	0.394
$lrDC\_sa\_c_{t-3}$	-11.862**	-15.269***	$lrDC\_sa\_sr_{t-3}$	0.013	-0.011
R^2	0.054	0.087	R^2	0.002	0.002
C	-0.183	0.133	C	-0.435	0.768**
$lrDC\_sa\_c_{t-4}$	-6.492	-19.391***	$lrDC\_sa\_sr_{t-4}$	0.018	-0.040*
R^2	0.016	0.143	R^2	0.004	0.022

Note: This table gives estimates for the following regressions:

$$D_t = \alpha + \beta lrX\_sa\_c_{t-i} + \mu, \tag{2.5.3}$$

$$D_t = \alpha + \beta lrX\_sa\_sr_{t-i} + \mu, \tag{2.5.4}$$

where $i = 1,2,3,4$, α is a constant, and β is the estimating coefficient. The dependent variable, D_t, is a monetary policy variable, DWG_t or DMP_t. The independent variable, $lrX\_sa\_c_t$ in model (2.5.3) is: cycle series of seasonally adjusted real net doemstic credit ($lrDC\_sa\_c_t$) or money (($lrM2\_sa\_c_t$)). The independent variable, $lrX\_sa\_sr_t$ in model (2.5.4) is: growth series of seasonally adjusted real doemstic credit ($lrDC\_sa\_sr_t$) or money (($lrM2\_sa\_sr_t$)). Significance levels: *10%, ** 5% , *** 1%.

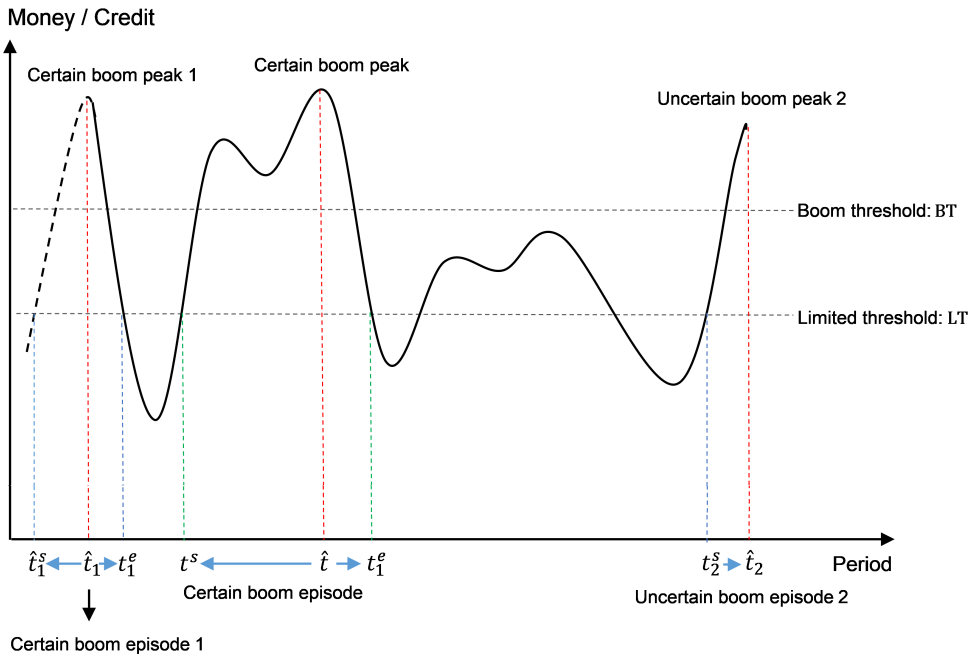
Appendix A

Credit Cycles in China

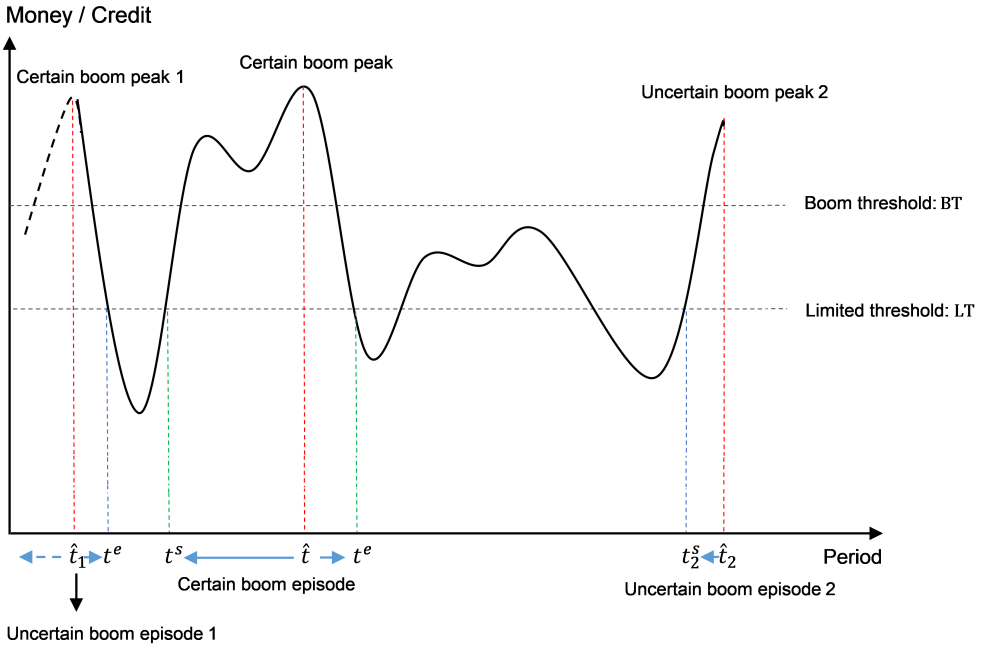
A.1 Examples for certain and uncertain booms

The following figures are several examples of certain and uncertain booms. In the figure, solid black line stands for credit or money series, and dashed balk line for the assumed part of the credit cycle series.

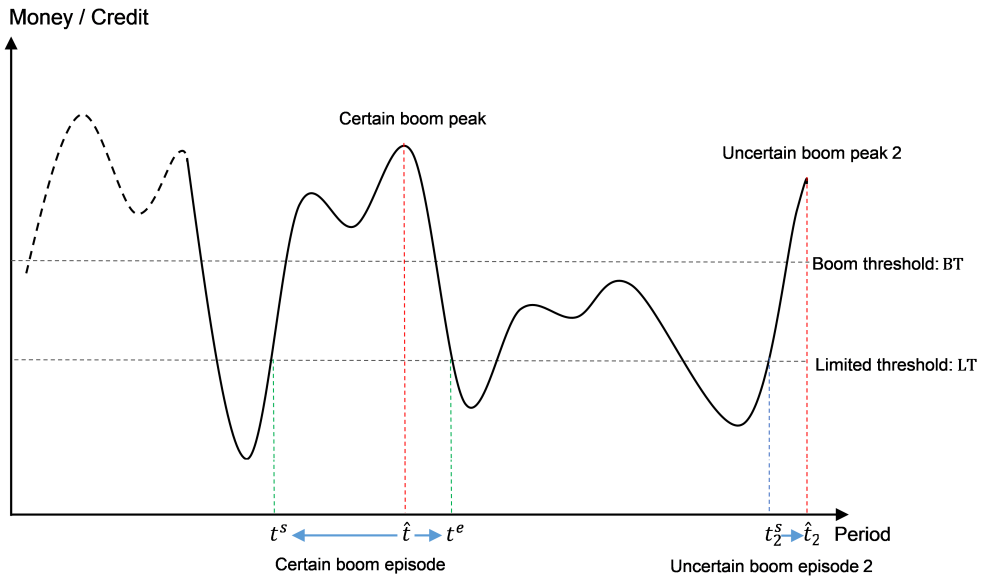
Example 1.



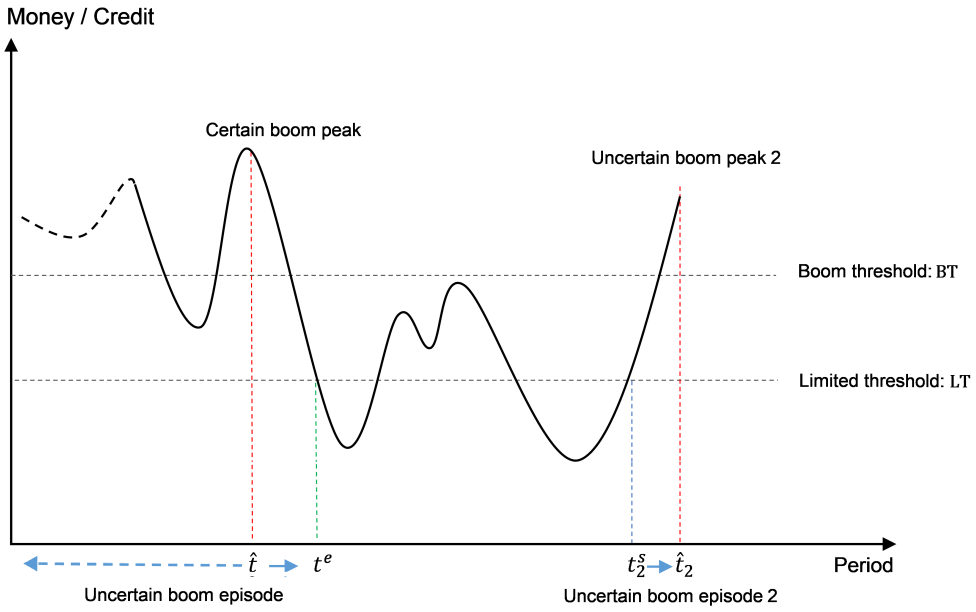
Example 2.



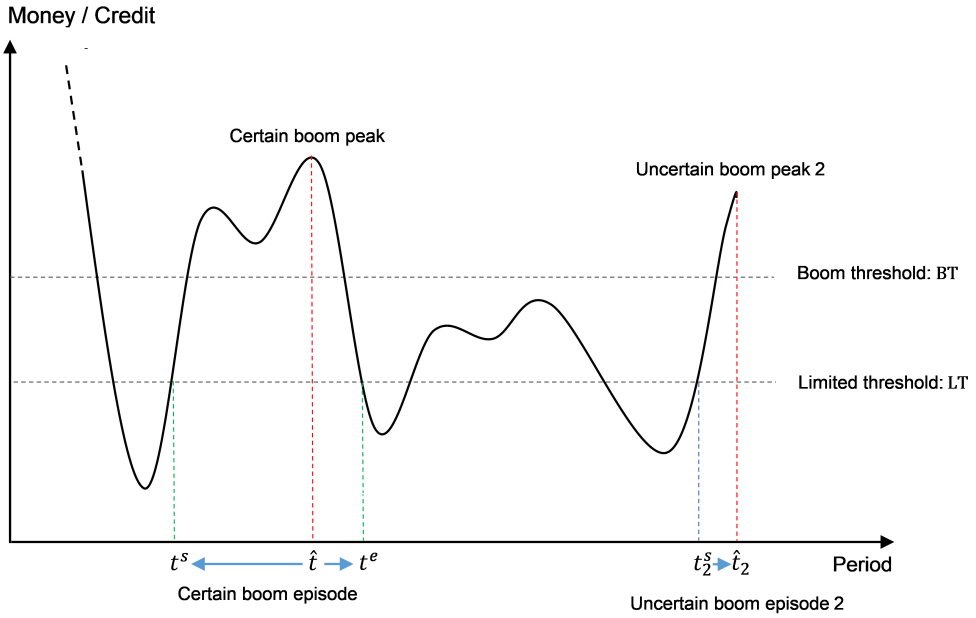
Example 3.



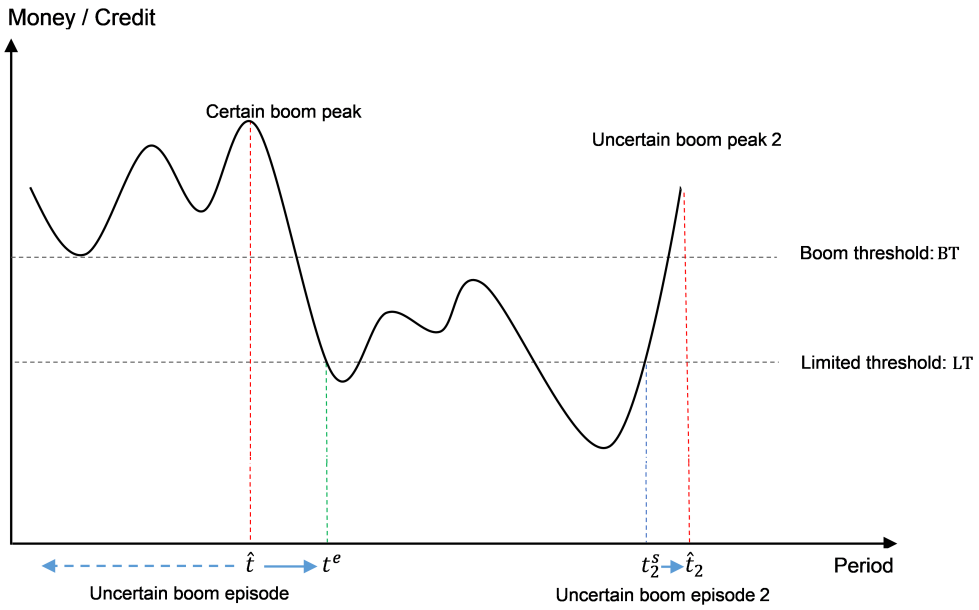
Example 4.



Example 5.



Example 6.



A.2 CPI calculation

Known:

- **CPI1 CPIo**: "CN: Consumer Price Index (2010=100)", 1986Q1-2018Q1, Not seasonally adjusted (NADJ), CEIC databse, SR92666437 (Code);
- **CPR**: "CH GDP: CONSUMPTION - PRIVATE CURN, Chinese yuan", 1980Q1-2018Q3, NADJ, Datastream, CHXCPN..A (Code)
- **rCPR**: "CH GDP: CONSUMPTION - PRIVATE (CON) CONN, Chinese yuan", NADJ, 1980Q1-2018Q3, Datastream, CHXCPR..(Code)
- **Dp**: "CN: The Rate of Inflation", 1979Q2-2016Q4, Seasonally ajusted (SA), Mohaddes and Raissi (2018) (MR).
- Inflation rate:
  - **quarterly inflation in percent quarterly rates**:

$$\pi_t^q = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} * 100 \approx (lnCPI_t - lnCPI_{t-1}) * 100.$$

– **quarterly inflation in percent annual rates** (Unit which is measured is percent at annual rates; Period over which is measured is quarterly change.):

$$\pi_t^{q^a} = \pi_t^q * 4.$$

For example, when we borrow from bank or lend to bank for a quarter (3 months), we do not say "the lending rate in percent quarterly rates", we often say "the lending rate in percent annual rates". We often talk about "inflation in percent annual rates", rather than "in flation in percent quarterly rates". "quarterly inflation in percent annual rates" is often used.

– **annual inflation in percent annual rates** (Unit which is measured is percent at annual rates; Period over which is measured is annual change.):

$$\begin{aligned}\pi_t^y &= \frac{CPI_t - CPI_{t-4}}{CPI_{t-4}} * 100 \\ &\approx (lnCPI_t - lnCPI_{t-4}) * 100 \\ &\approx ((lnCPI_t - lnCPI_{t-1}) + (lnCPI_{t-1} - lnCPI_{t-2}) \\ &+ (lnCPI_{t-2} - lnCPI_{t-3}) + (lnCPI_{t-3} - lnCPI_{t-4})) * 100 \\ &\approx \pi_t^q + \pi_{t-1}^q + \pi_{t-2}^q + \pi_{t-3}^q,\end{aligned}$$

$$\pi_t^y \neq \pi_t^{q^a}.$$

It does not matter whether π_t^y is seasonally adjusted, because it is annual inflation.

Calculation:

- $CPI2(CPIc) = \frac{CPR}{rCPR} * 100$, NADJ.
- Set a new series: $lnCPI3$, Seasonally adjusted, and $lnCPI3_{t=1979Q1} = 1$, then,
  $lnCPI3_{t=1979Q2} = lnCPI3_{t=1979Q1} + Dp_{t=1979Q2}$,
  $lnCPI3_{t=1979Q3} = lnCPI3_{t=1979Q2} + Dp_{t=1979Q3}$,
  ...
  $lnCPI3_t = lnCPI3_{t-1} + Dp_t$,
  ...
  $lnCPI3_{t=2016Q4} = lnCPI3_{t=2016Q3} + Dp_{t=2016Q4}$.
- Set a new series: lnCPI4, Seasonally adjusted. We want to get $lnCPI4_{t=2010Q1} = 1$, then,
  $lnCPI4_{t=1979Q1} = lnCPI3_{t=1979Q1} - lnCPI3_{t=2010Q1}$,

$lnCPI4_{t=1979Q2} = lnCPI3_{t=1979Q2} - lnCPI3_{t=2010Q1}$,
$lnCPI4_{t=1979Q3} = lnCPI3_{t=1979Q3} - lnCPI3_{t=2010Q1}$,
...
$lnCPI4_t = lnCPI3_t - lnCPI3_{t=2010Q1}$,
...
$lnCPI4_{t=2010Q1} = lnCPI3_{t=2010Q1} - lnCPI3_{t=2010Q1} = 0$, making $exp^{lnCPI4_{t=2010Q1}} = 1$,
...
$lnCPI4_{t=2016Q4} = lnCPI3_{t=2016Q4} - lnCPI3_{t=2010Q1}$.

- To get a new series $CPI4_{t=2010Q1} = 100$, Seasonally adjusted,
  $CPI4_t = exp^{lnCPI4_t} * 100$ (1979Q2-2016Q4)
- Set a new series: **CPIu**, Seasonally adjusted, then,
  - For 1979Q2-2016Q4, $CPIu_t = CPI4_t$;
  - For 2017Q1-2018Q1,
    $CPIu_{t=2017Q1} = CPIu_{t=2016Q1} * (CPI1_{t=2017Q1}/CPI1_{t=2016Q1})$,
    ...
    $CPIu_t = CPIu_{t-4} * (CPI1_t/CPI1_{t-4})$,
    ...
    $CPIu_{t=2018Q1} = CPIu_{t=2017Q1} * (CPI1_{t=2018Q1}/CPI1_{t=2017Q1})$,
  - For 2018Q2-2018Q3,
    $CPIu_{t=2018Q2} = CPIu_{t=2017Q2} * (CPI2_{t=2018Q2}/CPI1_{t=2017Q2})$,
    $CPIu_{t=2018Q3} = CPIu_{t=2017Q3} * (CPI2_{t=2018Q3}/CPI1_{t=2017Q3})$.
- **Note:** (i) quarterly inflation rate: $Dp = lnCPI4_t - lnCPI4_{t-1}$;
  (ii) quarterly inflation expressed at percent annual inflation rates: $100 * 4 * Dp$;
  - 100, to turn it into percent,
  - 4, to turn it from quarter to annual expression.

(iii)

$$\begin{aligned}\pi_t^y &\approx (lnCPI4_t - lnCPI4_{t-4}) * 100 \\ &\approx (Dp_t + Dp_{t-1} + Dp_{t-2} + Dp_{t-3}) * 100 \\ &\approx Dp_t * 100 + (Dp_{t-1} + Dp_{t-2} + Dp_{t-3}) * 100 \\ &\approx \pi_t^q + \pi_{t-1}^q + \pi_{t-2}^q + \pi_{t-3}^q.\end{aligned} \tag{A.2.1}$$

Get:

- $CPIu$,
- $\pi_t^q = Dp * 100$, $\pi_t^{q^a} = Dp * 100 * 4$,
- π_t^y,
$$\pi_t^y = \frac{CPIu_t - CPIu_{t-4}}{CPIu_{t-4}} * 100 \approx (lnCPIu_t - lnCPIu_{t-4}) * 100,$$
- $CPIu$, π_t^q, $\pi_t^{q^a}$, and π_t^y are all seasonally adjusted.

Then, turn real terms into nominal terms

- turn lending interest rate ($LINR_t$, %) to real interest rate ($rINR_t$, %):

$$rINR_t = INR_t - \pi_t^{q^a},$$

or,

$$rINR_t = INR_t - \pi_t^y.$$

$LINR_t$ can be seasonally adjusted (SA) or not seasonally adjusted (NADJ). If $LINR_t$ is seasonally adjusted, then $rINR_t$ is seasonally adjusted and we do not need to seasonally adjust $rINR_t$. If $LINR_t$ is not seasonally adjusted, then $rINR_t$ is not, and we need to seasonally adjust $rINR_t$. We could use annual inflation in percent annual rates, π_t^y, to turn nominal terms into real terms, because π_t^y is usually smoother than $\pi_t^{q^a}$. But we could use both π_t^y and $\pi_t^{q^a}$ to turn nominal terms into real terms and compare their difference.

- turn nominal macro variable X_t to real macro variable rX_t:

$$rX_t = \frac{X_t}{CPIu} * 100.$$

X_t can be seasonally adjusted (SA) or not seasonally adjusted (NADJ). If X_t is seasonally adjusted, then rX_t is seasonally adjusted and we do not need to seasonally adjust

rX_t. If X_t is not seasonally adjusted, then rX_t is not, and we need to seasonally adjust rX_t.

We can find real GDP (rY_t^{def}) data directly from database and it is given by,

$$rY_t^{def} = \frac{Y_t}{GDPdeflator} * 100.$$

We could use rY_t^{def} directly in the paper (make some notes in the paper), and we can compare rY_t^{def} with,

$$rY_t^{CPIu} = \frac{Y_t}{CPIu} * 100.$$

We can also compare GDP deflator (need the price in 2010Q1 is 100) with CPIu.

A.3 Comparing the Chinese credit data reported by PBoC with that by the Wold Bank

Since 2002, the Chinese central bank has revised the system of monetary and financial statistics, the PBoC's "All Accounts" financial reporting system, in line with the IMF Manual on Monetary and Financial Statistics, which allows to compare China's credit with some other countries using the similar credit definitions. As of 2002, the monetary statistics would not be fully compatible with historical statistics due to the revision to the system of monetary and financial statistics in year 2002. The following part compares the credit definition of PBoC with those of World Bank.

- **Domestic credit (DC)**. The China's quarterly series of domestic credit in the CEIC database matches both the net domestic credit and the domestic credit provided by the financial sector series in the World Bank Database. The World Bank metadata defines net domestic credit as the sum of net claims on the central government and claims on other sectors of the domestic economy (IFS line 32). Credit instruments include loans, debt securities, equities and investment fund shares, etc.

  According to World Bank Metadata, domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension

funds, and foreign exchange companies. The PBoC's meatadata on domestic credit is similar with the World Bank Metadata.

- **Claims on private sector (CLP)**. China's CLP series in the CEIC database is the same as the domestic credit to private sector in the World Bank database.

  According to the World Bank Metadata, domestic credit to private sector (IFS line 32D..ZK or 32D..ZF) includes gross credit from the financial system, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment, to individuals, enterprises, nonfinancial public entities not included under net domestic credit, and financial institutions not included elsewhere. The PBoC's metadata on domestic credit is similar with the World Bank Metadata.

Chapter 3

Bank-specific Determinants of Loans Growth in China

3.1 Introduction

This chapter investigates the determinants of bank lending in China in a post-crisis environment, 2008-2018. We conduct a heterogeneous panel analysis of a panel of 14 Chinese listed banks, for which there is data over the period 2008Q1-2018Q4. These 14 banks represent a large share of China's banking financial system. We group them into various bank-clusters, classified by Chinese government categories and global systemic importance.

Under a market system loan growth responds to stochastic economic shocks to demand and supply and tends to follow a random walk like path, similar to many other financial variables, within regulatory constraints. Under planned systems loan growth is much more predictable. A comparison of the sterling exchange rate with renminbi exchange rate will show the difference. In the case of the banks, the planning controls include plan targets, credit restrictions and loan quotas. The possible determinants of loan growth are divided into two sets of variables. The first set, we label *bureaucratic variables*. These include deterministic elements like trends, seasonal effects and dummies representing state directives during the crisis plus a lagged dependent variable reflecting inertia or slow adjustment. The second set we label *economic variables*. These include bank-specific economic factors that in a market system one would expect to influence loan growth. The economic variables we consider are suggested by the US bank regulators financial conditions measures usually summarized as CAMEL: *C*apital adequacy, *A*sset quality, *M*anagement capability, *E*arnings and *L*iquidity, plus some other variables like bank size. We find that for individual banks and bank groups bureaucratic variables are very significant and the economic variables have comparatively little influence, which is consistent with the state retraining quite a lot of

control. However, pooling of the data, which constrain the coefficients to be the same across banks within a group, gives more evidence for the influence of economic variables. The size of the coefficients is similar to the average of the individual banks but they are now significant, reflecting the larger sample size. Thus the pooled estimates are somewhat more supportive of the role of bank-specific market forces in determining loan growth. However, the bureaucratic variables remain important.

China's banking financial institutions accounted for 78% of total financial assets in 2008 and 83% in 2018. Commercial banks are the main part of Chinese banking financial institutions and their total assets occupied 78% of the banking financial institutions in 2018, and is therefore a pivotal part of China's financial system. Chinese commercial banks rely on traditional investment tools, predominantly lending, which reached 52% of their total assets in 2018. The evolution of bank lending is hence clearly at the core of recent Chinese financial development. So this chapter investigates the determinants of loan growth for 14 listed Chinese commercial banks over the period 2008-2018, the decade after the financial crisis.

China initiated a series of far reaching financial reforms in 1978 in an attempt to transform gradually from a government-controlled financial system to a market-based financial system, which lets the market play decisive role in resource allocation. The main purpose of these reforms has been to increase competition, enhance stability, and improve the performance of the Chinese banking sector; and indeed, competition has increased significantly (Tan and Floros, 2018). As far as the reforms of the financial system are concerned, three important aspects of financial institutional changes are: (i) the reform of the banking system; (ii) the exchange rate reform; and (iii) the rapid development of the capital market (Zuo and Park, 2011). Given the importance of banking to the Chinese economy, reforms of the banking system took a centre stage in the wider reform effort to achieve China's transformation to a market economy. This included the development of a multi-tiered banking system of private and state-owned banks from the pre 1978 banking system, where lending was fascilitated through the People's Bank of China only. In investigating determinants of bank lending in China we hence give an evaluation of the state of this development thus far. The rapid development of China's financial system implied rapid loan growth. There is a debate as to whether this loan growth is justified by market forces or a result of state interventions, which goes to the core of arguments on sustainability of the Chinese banking system. We investigate this issue.

A crucial function of a financial system is its ability to withstand shocks. Open, market based systems are vulnerable to financial market disruption: Lack of control and interconnectedness of market participants can lead to rapid transmission and amplification of external

shocks. The financial crisis of 2008 and following gave an example of unusually large disruption to global financial markets. It was therefore a test to China's developing financial system. Disruptive effects to the global financial system transmitted in large part through bank lending: Across the world the failure of traditional bank-lending channels of monetary transmission prompted the implementation of unconventional monetary policies, such as quantitative easing, by major central banks. Investigating Chinese post-crisis bank lending has important implications for the stability of China's financial system, which in late 2019 was an important policy question.

The remainder of the paper is organized as follows. We present a literature review in Section 3.2. We have had an overview of Chinese financial market reforms in Chapter 1 and we described particularly about the 14 Chinese listed banks in Section 3.3 this chapter focuses. We describe the data and variables in Section 3.4. We discuss the empirical methodology and results in Section 3.5. Section 3.5 presents the empirical findings. Section 3.6 concludes.

3.2 Literature review

While there is a large literature on the determinants of international bank lending, concerned with distinguishing the external (foreign "push") and internal (domestic "pull") factors, (e.g. De Haas and Van Lelyveld, 2006; Gozgor, 2014; Iwanicz-Drozdowska and Witkowski, 2016; Jeanneau and Micu, 2002), it is not very relevant for Chinese domestic lending. China's banking system is highly controlled by government and banks' lending behaviour follows the lead of government. Similarly, there are a number of studies of the determinants of credit growth in panels of countries which regard China as an observation in their samples, for instance, Takáts (2010) and Gozgor (2014). However, studies including China as an observation ignore the heterogeneity across countries.What is true from other economies and groups of countries may not be true for China.

Another part of the literature is concerned with distinguishing the demand and supply-side factors driving loans growth. Some variables, e.g., lending interest rate, inflation, debt overhang and alternative funding, are usually treated as factors affecting credit demand. Some other macroeconomic variables, e.g., real GDP, unemployment, wages, economic sentiment index, stock exchange, etc. However, it is often difficult to separate macro variables into demand-side or supply-side factors. For example, real GDP drives credit cycles through both supply and demand channels. We focus on bank-specific variable driving loan growth. These variables, such as bank size, capital adequacy, asset quality, earnings, liquidity and funding, will reflect both demand and supply side macroeconomic forces.

The large literature emphasizing the central role of the government on Chinese banking is particularly relevant to our analysis. Firth et al. (2009) point out that a salient characteristic of China's banking sector is the dominant state ownership of banks, which allows for government involvement in the decision making of those banks, and policy lending remains a defining characteristic of the banking system. Liu et al. (2018) point out that the banking system in China is mostly controlled by the government, and the Chinese capital market and credit supply expansion provide an excellent environment which cannot be replicated in other countries. Firms in China are more bank dependent, which makes them much more sensitive to changes in bank loan supply. Liu and Wray (2010) argue that domestic Chinese banks really do follow the lead of the government, — when encouraged to lend, they do so; when lending is discouraged, they impose self-constraint. Bailey et al. (2011) state that China's banks remain largely constrained by government intervention at different levels and subject to substantial political influences. Zhang and Daly (2011) argue that the government influences the banks' lending behaviour by controlling the amount of lending through quotas and other means to some degree, for example, state-owned banks (policy banks and "big four" state-owned commercial banks) are the major lenders of state-owned enterprises. The SOEs make up a substantial part of the national economy in China (Xu, 2010). So far China's financial system is still a typical "financial repression": banking is at the core of China's financial system; what makes things worse is that most banks are state-owned banks; China's interest rate has been regulated; and China's stock market is still highly regulated (Liu, 2014).

Ru (2018) examines effects of government-directed lending on firms using detailed industrial loan data from China Development Bank (CDB) and finds that CDB industrial loans to state-owned enterprises (SOEs) crowd out private firms in the same industry but crowd in private firms in downstream industries. Liu et al. (2018) examine effectiveness of the government oriented economic stimulus package and the associated increase in bank loans supply by using a panel of Chinese firms over the period 2003-2013 and find that SOEs received more bank loans and resources than non-SOEs. Cheng and Degryse (2010) investigate whether financial development affects local economic growth, and they find that bank development, in particular bank credit, greatly contributes to province growth. There are also research exploring loans allocation in China from the standpoint of banks making loan decisions or from the standpoint of firms accessing loans. For example, Firth et al. (2009) examine how the Chinese state-owned banks allocate loans to private sectors and they find that the banks use commercial judgments to make loan decisions and political connections play a role in gaining access to bank finance. Other examples of research on loans allocation are Cull et al. (2015) and Dong et al. (2016). In addition, for the case of banks in China, some researchers focus on studying determinants of banks' low profitability

(García-Herrero et al., 2009); relationships of bank profitability with inflation and economic growth (Tan and Floros, 2012); determinants of banking efficiency (Chen et al., 2005); bank ownership reform and bank performance (Lin and Zhang, 2009); determinants of financial performance (Heffernan and Fu, 2010).

There is also a literature examining the effect of bank lending. Liang and Cao (2007) investigate the time series relationship between property prices and bank lending in China over the period 1999Q1-2006Q2 by using an autoregressive distributed lag framework and find that there only exists unidirectional causality running from bank lending to property prices. Pan and Yu (2008) study empirically the impact of local government intervention, legal enforcement, and financial weakness on the bank loans of the state-owned listing companies controlled by provincial government, and they find that the legal enforcement and financial development at the province level have negative impact on bank credit and debt maturity. Liu and Wray (2010) explore the effects of excessive liquidity on bank lending in China and they think that it is not excessive liquidity that creates the skyrocketing domestic loan growth. Huang et al. (2015) explore how the bank loans and local amenities explain Chinese urban house prices and he point out that credit drives up property prices after 2008 financial crisis, whereas house prices only influence bank lending before crisis. Mixed results have been obtained because of differences in research perspectives on loans determinants in China, theoretical frameworks, econometric estimation methods, and dataset.

The ties with government vary across bank groups. The government intervenes in various ways including credit quotas, monetary policy, window guidance, etc. Thus it is difficult to measure government intervention. Therefore, many researchers just simply attributed loans growth to government decisions. However, we think that even though the government lending policies dominated, the banking institutions can have some freedom to make decisions according to market rules. Even though government sometimes makes specific lending decisions for banks, it generally shows lending directions macroeconomically and it does not intend to control loans in detail. Especially, the Chinese government has been implementing a series of financial liberation reforms in recent years.

There is overwhelming evidence for other regions and countries that bank-specific factors play an role in determining loans growth. The determining factors of credit fluctuations detected varied across studies, depending on sample and data period. Everaert et al. (2015) analyse demand and supply factors (including bank size, asset quality, financial leverage indicator, liquidity, capital adequacy, and profitability indicator) driving credit cycles in the Central, Eastern, and south-eastern Europe (CESEE) countries by focusing on a large sample of bank-level data on credit growth. Their results of panel data analysis indicate that supply factors, on average and relative to demand factors, gained in importance in explaining

credit growth in the post-crisis period. Both CESEE countries and China have undeveloped financial market, but they are quite different in economy size, party and capitalist systems. It is not easy to compare studies about CESEE countries with China. Pham (2015) empirically investigates possible factors including capital requirements, bank profitability, bank asset quality and bank concentration, which drive domestic credit across 146 countries at different levels of economic developments. They find that credit supply is negatively related to capital requirement, exchange rate, index of capital account openness, bank concentration and non-performing loans; they also find evidence of the country specific effect of economic growth on bank lending; the determinant role of several variables such as inflation, global liquidity, ROE/ROA index on explaining bank credit growth was also explored. There are some recent studies on drivers of domestic credit expansion based on individual countries. Awdeh (2017) investigates causes of credit growth in Lebanon by proposing a panel estimation equation including a set of internal (bank-specific variables including growth of customer deposits, equity to asset ratio, loan-loss-provision, return of assets, and bank size) and external variables (factors reflecting economic environment and developments). The panel data is based on 34 commercial banks over the period 2000 to 2015. Awdeh (2017) finds that deposit growth, GDP growth, inflation, and money supply positively contribute to bank credit to the resident private sector. In contrary, credit risk, lending interest rate, T-bill rate, public borrowing, and remittance inflows decrease loan growth. The impact of one-year lag of each variable was also studied. Tan (2012) explores the determinants of the growth of private sector credit in Philippines and they find that relatively high net interest margins have been a significant deterrent and deposit expansion also contributes positively to private credit growth, while a larger bank size, bigger bank capitalization, foreign ownership, high overhead costs and presence of corporate taxes all positively contribute to higher net interest margins. These studies show evidence that bank-specific factors play a role in loans growth, but their research results are mixed across regions, sample period, definition of variables, control variables, research methods, etc. In addition, these studies usually include both bank-specific and macroeconomic variables in their models. China is quite different from other regions in country size, economic and political systems, and it will make sense to study bank-specific variables on the basis of balance sheets.

With this background, this study will systematically focus on identifying determinants of China's loan growth on the basis of panel data.

3.3 The state of China's banking system

This section gives an introduction to Chinese banking institutions, particularly the sample of 14 listed banks with data since the financial crisis.

At the end of 2018, there were 4588 banking financial institutions operating in China, including 6 large commercial banks (Postal Savings Bank of China joined in 2018), 12 joint-equity commercial banks, 134 city commercial banks, etc. In the same year, there were 46 banks listed on Chinese stock exchanges; we focus on the 14 of them, listed before 2009, to allow for long time series. There were 3 others listed in 2010, and the other 29 listed after 2013. On the basis of classification standard of Chinese government, our sample includes 3 groups of banks: 4 large state-owned commercial banks (SOCBs), 7 joint-equity commercial banks (JSCBs), and 3 city commercial banks (CCBs) (see Table 3.1). Since 2011, the Financial Stability Board has published a list of global systemically important banks (G-SIBs). Our sample includes 3 G-SIBs: Bank of China, China Construction Bank, Industrial and Commercial Bank of China; and 11 other banks which are not global systemically important banks (G-SUIBs). The following shows details of these banks (see Table 3.1).

Our sample has 4 of the 6 large state-owned commercial banks, which include 3 of the traditional "big four" state-owned commercial banks: Bank of China, China Construction Bank, Industrial and Commercial Bank of China,[1] and Bank of Communications. Large state-owned commercial banks are directly controlled by the state (Ministry of Finance and Cental Huijin Investment Co., Ltd.), which is the first majority shareholder. Zhang and Daly (2011) describe a large degree of government influence on the "big four" state-owned commercial banks. These banks further dominate the banking financial institutions in terms of assets share, capital source, network distribution, and stability. Their total assets comprises 36-51% of banking financial institutions each year from 2008-2017 (see Figure 3.1). Generally, State-owned banks are guaranteed by the Chinese government and enjoy a high reputation and much social resources. Their relative monopoly position allows them to capture a large market share in terms of assets outstanding. They run various and balanced business all over the country including major cities and most rural areas. Their strong and stable customer base gives them a big advantage in terms of stability of lending and deposit. Of the six large commercial banks in China, the four included in our sample account for 82-83% of total assets each year from 2008 to 2017.

Our sample also has 7 of the 12 joint-equity commercial banks, which includes 5 state-controlled banks which are SOEs: Shanghai Pudong Development Bank, Hua Xia Bank

[1] Our sample does not include Agricultural Bank of China, which was listed the Shanghai Stock Exchange in 2010.

Co., Ltd., China Merchants Bank, Industrial Bank Co., Ltd., and China CITIC Bank; and 2 non-state-controlled banks, which are private-owned enterprises (POEs): Ping An Bank Co., Ltd. and China Minsheng Banking Co., Ltd.. The joint-stock commercial banks run business mainly in large and medium-sized cities and a few county areas. They implement management differentiation strategy, provide unique services, and gradually form their own competitive advantage. Their market share measured by total assets ratio in the banking financial institutions has increased from 14% in 2008 to 18% in 2017 (see Figure 3.1). Of the 12 joint-equity commercial banks in China, the seven included in our sample account for 80-84% of total assets each year from 2008 to 2017.

Table 3.1 14 listed banks.

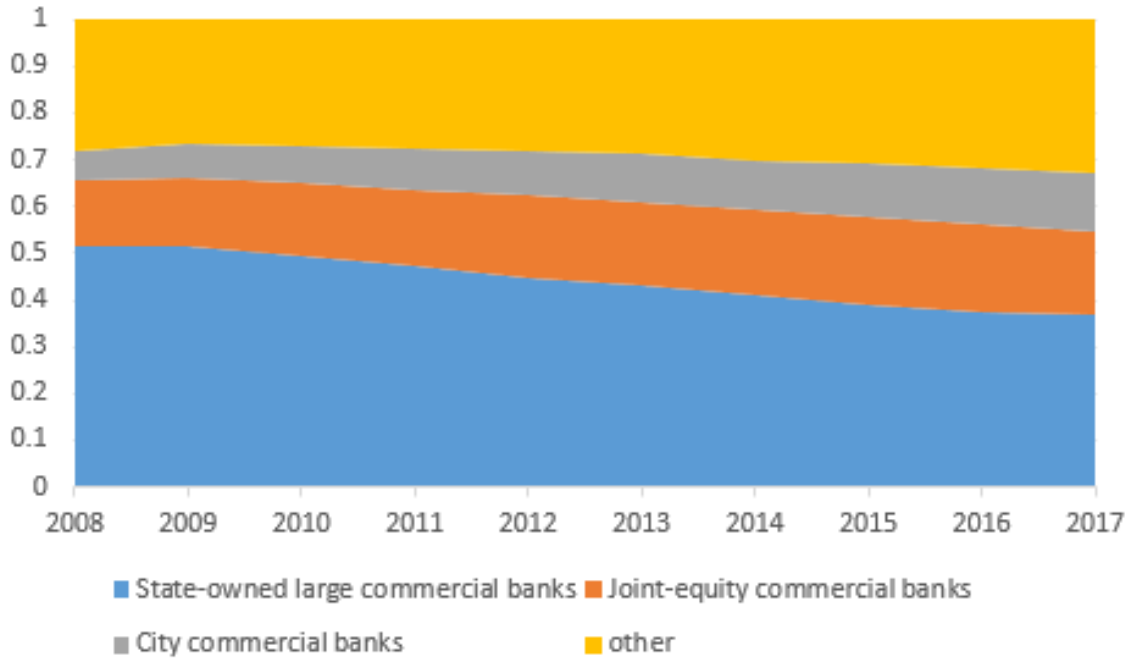
crossid	Stock code	Bank name	Chinese classification	Sytematic importance	Listing time
1	601398	Industrial and Commercial Bank of China Limited	SOCB	G-SIB	27/10/2006
2	601939	China Construction Bank	SOCB	G-SIB	27/10/2005
3	601988	Bank of China	SOCB	G-SIB	01/06/2006
4	601328	Bank of Communications	SOCB	G-SUIB	23/06/2005
5	000001	Ping An Bank Co., Ltd.	JECB	G-SUIB	10/03/1989
6	600000	Shanghai Pudong Development Bank	JECB	G-SUIB	23/09/1999
7	600015	Hua Xia Bank Co., Ltd.	JECB	G-SUIB	12/09/2003
8	600016	China Minsheng Banking Co., Ltd.	JECB	G-SUIB	19/12/2000
9	600036	China Merchants Bank	JECB	G-SUIB	09/04/2002
10	601166	Industrial Bank Co., Ltd.	JECB	G-SUIB	23/01/2007
11	601998	China CITIC Bank	JECB	G-SUIB	19/04/2007
12	601169	Bank of Beijing	CCB	G-SUIB	19/09/2007
13	601009	Bank of Nanjing	CCB	G-SUIB	19/07/2007
14	002142	Bank of Ningbo	CCB	G-SUIB	19/07/2007

Note 1: SOCB refers to the state-owned commercial bank; JECB refers to the joint-equity commercial bank; and CCB refers to the city commercial bank. G-SIB refers to the global systemically important bank and G-SUIB other banks.
Note 2: We got information of sample banks from CSMAR (the China Stock Market Series and the China Listed Firms Research Series), websites, the 2015 Annual Report of China Banking Regulatory Commision, China Financial Development Report (2016; 2017), and the 2017 Annual Report of China Banking Regulatory Commission.

Our sample also includes 3 of 134 city commercial banks including Bank of Ningbo, Bank of Nanjing, and Bank of Beijing. Bank of Ningbo ranks first in the list of city commercial banks (over 300 billion yuan in assets) in the competitiveness evaluation report of China's commercial banks released by The Banker in 2018. City commercial banks were founded gradually since 1995 on the basis of urban credit cooperatives. They mainly offer financial services for local middle and small enterprises and residents. Generally, they supply financial

services at provincial level although some have broken regional restrictions. City commercial banks have diverse ownership. Most city commercial banks have strong ties to their local government and are majorly or wholly state owned.[2] Even though the government is not the largest holder of some city commercial banks, the local government is de facto in control. The market share of city commercial banks has increased from 6% in 2008 to 13% in 2017. Of the 134 city commercial banks in China, the three included in our sample account for 14-16% of total assets each year from 2008 to 2017.

Fig. 3.1 Market (assets) share of banking financial institutions in China, 2008-2017.



Source: The 2017 Annual Report of China Banking Regulatory Commission.

Generally, the number of each type of banking financial institutions is not proportional to its market share. Even though the 14 sample banks occupy only a very small portion of all the 4588 banking financial institutions in terms of the number, they all are the main banking financial institutions with large assets.[3] The total assets of population of large commercial banks, joint-equity commercial banks, and city commercial banks is 169.5 trillion Yuan at end of 2017, and it is 67.15 percent of the total assets of all financial institutions. The total assets of 14 sample banks takes account of 46.52% of that of all financial institutions. Therefore,

[2] Banking in China, https://en.wikipedia.org/wiki/Banking_in_China.

[3] Rural commercial banks, rural cooperative banks, rural credit cooperations, and village banks have a large population number of 3822, but they usually have a very low market share.

regarding the market share of banks in the population of banking financial institutions, the selected banks are representative of the total population of banks.

3.4 Data

As noted in the introduction we distinguish bureaucratic and economic variables. The bureaucratic variables, representing government planning, are deterministic variables like trend, seasonals, and dummy variables for crisis regulations plus a lagged dependent variable to represent inertia. The economic variables are discussed below.

3.4.1 Economic determinants using CAMEL framework

In this chapter, our interest lies in the loan growth of 14 listed Chinese banks. We obtain bank-level data over the period 2008Q1-2018Q4 from CSMAR (the China Stock Market Series and the China Listed Firms Research Series).[4] We also collected additional information online.

The dependent variable in our models is loan growth, which is the percent change of net loans and receivables at quarterly rate. Net loans and receivables is the monetary value of outstanding loans and discounted assets receivables after deducting the provision for impairment at the end of period. We use the CAMEL framework, which was recommended by the U.S. Federal Reserve, to suggest the explanatory variables, reflecting five areas of financial conditions for a financial institution: *C*apital adequacy, *A*sset quality, *M*anagement capability, *E*arnings and *L*iquidity.[5] CAMEL is set out in Table 3.2, together with the proxies that we use to represent each variable. There is an element of judgment in how one chooses to measure each element in CAMEL and different authors choose different variables. Our choice is not exactly the same as used in the United States. We also add bank size which was suggested to affect loan growth.

In the following, we discuss how CAMEL variables may influence the dependent variable, loan growth, and the expected sign of impacts is shown in Table 3.2.

[4] Dungey and Osborn (2019) cited: although there is considerable debate in the literature about the quality of Chinese data, Sinclair (2013) shows that the extent of data revisions is comparable to those for the US; and similarly, Chow (2006) finds official China data to be at least reasonably accurate and are reliable for use in many macroeconomic analyses. The assigned staff members are obligated by law to prepare accurate statistics.

[5] In 1995 the Federal Reserve and the Office of the Comptroller of the Currency replaced CAMEL with CAMELS, adding *S*ensitivity to Market Risk. Sensitivity to market risk is a complex and evolving measurement area, and it primarily to address interest rate risk, the sensitivity of all loans and deposits to relatively abrupt and unexpected shifts in interest rates. Given no available data for individual bank's interest rates for the whole period, 2008Q1-2018Q4, we do not include this in our paper.

Table 3.2 CAMELS variables.

CAMEL	Variable	Abbr.	Unit	Expected sign
Dependent variable	Growth of Net Loans and Receivables	NLG	1	
Capital Adequacy	Ratio of Equity to Assets	ETA	1	+
Asset quality	Ratio of General Risk Reserves to sum of General Risk Reserves and Net Loans and Receivables	GRRTTL	1	+
Management	Net Profits per Employee	NPTEMP	RMB	+
Earnings	Return on Equity	ROE	1	+
Liquidity	Ratio of Cash to Assets	CTA	1	+
	Ratio of Deposits Due To Customers to Total Assets	DCTTA	1	+

3.4.1.1 Capital adequacy

Capital adequacy is measured as equity to assets ratio. Equity is the money that investors have put into the banks (by buying its stock). It is a potential form of funding (Brinkmeyer, 2015). The equity to assets ratio measures a bank's capital adequacy and indicates a bank's leverage (debt). More specifically, it measures the degree to which a bank is financing its operations through debt versus wholly-owned funds. It reflects the ability of shareholder to cover all outstanding debts in the event of a business downturn.

A high ratio implies the bank is well capitalized and relies little on debt to run its business. Relying too heavily on debt, the bank has to make more interest payments, weakening its financial position and making it vulnerable to a bank run, at which point it won't be able to pay out deposits. Bank loan is a major part of domestic credit. De Lis et al. (2001) find that episodes of strong credit growth tend to go hand in hand with large increases in equity in a sample of industrial countries. This ratio is expected to be positively related to loan growth. Everaert et al. (2015) assess capital adequacy of banks by ratio of equity to net loans and they find that capital adequacy in the previous year has a positive effect on real annual credit growth in Central, Eastern, and Southeastern Europe.

The capital adequacy is hence expected to have a positive effect on loan growth of Chinese banks.

3.4.1.2 Asset quality

Researchers use the ratio of loan loss reserves (memo) to gross loans to measure asset quality, which indicates how much of the total portfolio has been provided for but not charged off (Everaert et al., 2015; Kosmidou et al., 2005; World-Bank, 2006). Loan loss reserves are accounting entries banks make to cover estimated losses on loans due to defaults and nonpayment. Given data availability, we use the ratio of general risk reserves to the sum

of general risk reserves and net loans and receivables to measure asset quality of a bank. General risk reserves refers to the risk preparation that a bank extracts from the net profit to make up for the unrecognized potential loss.

Chinese banks assess the potential risk of some risky assets using their own developed models based on the principle of dynamic provision, or by the government requirements. Dynamic provision refers to the counter-cyclical provision method adopted by banks according to the changes of the macroeconomic situation. That is, when the default rate of the risky assets is relatively low in the upward macroeconomic trend, banks make more reserves to increase financial buffers. When the default rate of the risky assets is relatively high in recessions, banks make less reserves and use the accumulated provisions to absorb asset losses. Loans are the major asset for most banks. So the ratio of general risk reserves to the sum of general risk reserves and net loans and receivables measures the asset quality, particularly loan quality: the higher the ratio, the less risky assets, the better the quality of the assets including the loan portfolio.

Asset quality is hence expected to have a positive effect on loan growth because lending is inversely related to risk (Altunbas et al., 2007; Nier and Zicchino, 2008).

3.4.1.3 Management

Management influences whether a bank possesses the ability to correctly diagnose and respond to financial stress. The category depends on the quality of the business strategy, financial performance areas, and internal control measures. In the business strategy and financial performance areas, it refers to the institution's plans for the next few years, including the capital accumulation rate, growth rate, and identification of the major risks. Internal control measures refers to the its ability to track and identify potential risks. Examples includes information systems, audit programs, and record keeping.

Management is measured as net profits per employee. In CAMEL model studies, Soni (2012) use total debt to total deposits, profit per employee, ROE, and earnings per employee as indicators of management of a bank. Rostami (2015) uses net profit, total assets, total liabilities, total deposits, and total loans of number of branches of each bank. Given the definitions of management, strong correlations of indicators employed by researchers and data availability, we use net profits per employee to measure management.

Net profits per employee is expected to have a positive effect on loan growth of Chinese banks.

3.4.1.4 Earnings

Earnings are measured as return on equity. Return on equity is equal to net profits divided by balance of shareholders' equity, which measures how profitable a bank uses its capital. It provides a solid indicator of earnings and profitability performance of banks and is a very effective metric for evaluating and comparing banks. ROEs of 15-20% are generally considered to be favorable for purposes of investment.[6]

A higher profitability is a signal of a general improvement of economic conditions. A higher return on equity indicates that a bank is effectively using its capital to generate profits and return the profits to investors at an attractive level. From this point, a higher return on equity can attract more equity and then a bank have a higher capital adequacy which is expected to have a positive effect on loan growth. Low profitability may signal fundamental problems for insurance corporations and may be considered as a leading indicator for solvency problems (Heath, 2013), which we think also works for banks. Intuitively, banks will conceivably lend more as their profitability increases.

Return on equity is expected to have a positive effect on loan growth of Chinese banks.

3.4.1.5 Liquidity

Liquidity is measured as ratio of cash to assets. We use information from Financial Dictionary, Investopedia, and the Economic Times to understand liquidity of a bank.[7] Liquidity is the ability of a bank to pay its debts using only its liquid assets. A liquid asset can be easily sold or converted into cash to meet financial obligations on short notice at little or no loss of its value. Funds in checking, cash in banking accounts and marketable securities, such as stocks and bonds, are the most common types of liquid assets for all businesses including banks. So, ratio of cash to assets is an indicator to reflect the degree of a bank's assets liquidity.

Higher available liquidity in the preceding period is expected to facilitate greater credit expansion (Everaert et al., 2015). High liquidity implies that the bank has a good ability to pay its debts. However, it does not mean that, the more liquid assets a bank has, the more benefit it gets. In the operation of banks, they try to expand loans and investments for profit. Meanwhile, banks are required to keep enough liquid assets to pay its debts to avoid the accumulation of liquidity shortfall. Liquidity shortfall can trigger banks' operation risk and even risks in the financial system.

[6] See Investopedia, https://www.investopedia.com/ask/answers/040815/what-level-return-equity-common-company-banking-sector.asp

[7] Financial dictionary, http://financial-dictionary.thefreedictionary.com/liquid+asset. Investopedia, http://www.investopedia.com/ask/answers/052515/what-difference-between-banks-liquidity-and-its-liquid-assets.asp. The Economic Times, http://economictimes.indiatimes.com/definition/liquid-asset.

Because lending is inversely related to risk, liquidity measured by cash to assets ratio is expected to have a positive effect on loan growth of Chinese banks.

3.4.1.6 Funding situation

We use the ratio of total customer deposits to total assets as a measure for a bank's funding situation. This ratio measures what percentage of total assets is supported with customer deposits. Customer deposits refers to savings deposits except due to banks and other financial institutions, which is a insured funding. Short-term funding includes deposits from banks, and other deposits and short-term borrowings, which is uninsured funding. The share of customer deposits in total assets captures the insured funding, while the share of short-term funding in total assets captures the uninsured funding (Brinkmeyer, 2015). Insured funding is relatively cheap and rise of insured funding decreases a bank's cost. Customer deposits is the least expensive funding source for a bank.[8] A higher share of customer deposits means a better funding situation, which might promote bank loans.

A better funding situation of a bank is expected to increase the loan growth.

3.4.1.7 Bank size

We control for banks' size, using total assets of a bank over total assets of the 14 sample banks. The share of total assets of a bank shows the position of the bank in the banking sector (Iwanicz-Drozdowska and Witkowski, 2016; Micco and Panizza, 2006).

Many researchers measure bank size on the basis of a bank's total assets, but their specific technologies are different. De Haas and Van Lelyveld (2006) use the portion of a bank's total assets in the total assets in the banking sector in a particular country to measure bank size, which is similar to our measurement. There are also researchers who measure bank size by taking the natural logarithm of total assets (Altunbas et al., 2007; Brinkmeyer, 2015; Chen and Wu, 2014; Kim and Sohn, 2017). Everaert et al. (2015) treat bank assets-to-GDP (bank size) as a explanatory variable of credit growth and find that larger banks grow more slowly than smaller ones.

Altunbas et al. (2007) find that bank asset size seems to be important as large commercial banks appear to be less risky than their smaller counterparts and bigger efficient and inefficient banks also seem to have lower loan loss reserve levels. So, it seems that larger banks have higher loan growth. Banks with a small share may lend aggressively to increase their market stake. On the other hand, banks with a high market share may enjoy their 'monopolistic' position and impose their conditions on the credit market. So Iwanicz-Drozdowska and

[8] See the Annual Report Pursuant to Section 13 or 15 (d) of the Securities Exchange Act of 1934 (2018): http://investors.cryolife.com/static-files/6ef9d21c-da5c-4d7e-9bba-70c04f8f4612.

Witkowski (2016) believe that the influence of the share of a given bank on its credit growth may be non-linear and, most of all, that it is rather the 'category' (e.g., small or quasi-monopolistic) that matters, not the share in quantitative terms. Kim and Sohn (2017) argue that the expected sign of bank size on lending activities is ambiguous. According to the "too big to fail" theory, Kim and Sohn (2017) argue that, large banks have incentives to take more risk amid high expectations of government bailout to prevent systemic risk, thereby enabling supply of more credit. However, large banks can diversify their portfolio by investing in various types of securities and involving themselves in various activities, whereas small banks tend to pursue traditional lending activities. From this perspective, the bank size effect can be negative.

So there is so far no consistent finding about the size effect, but current research shows that bank size makes some difference for loan growth. The effects of bank size on loan growth is expected to depend on the relative strength of its positive and negative effects.

3.4.2 Data description

Table 3.3 and 3.4 present the mean and standard deviation of the variables, which reflects financial conditions of banks, over the period from 2008Q1 to 2018Q4. Figure 3.2 and Figures B.1-B.8 in Appendix show the patterns of variables. The financial conditions vary across banks and groups of banks.

Comparing bank groups classified by Chinese standard, on average, state-owned commercial banks are the largest and have the lowest loan growth (3.25%). This is in line with state-owned commercial banks having the lowest general risk reserve ratio, net profit per employee, as well as liquidity measured by cash-to-assets. State-owned commercial banks have the highest capital adequacy and a good situation with respect to their insured funding measured by the share of customer deposits in total assets. State-owned commercial banks rely on traditional investment (loans) and funding instruments (customer deposits). For all variables excluding ROE and bank size listed in Table 3.4, state-owned commercial banks shows stability in terms of their smallest standard deviations among three bank groups. Joint-equity commercial banks have an average loan growth of 4.35%. On average estimates for joint-equity commercial banks are in between large state-owned commercial banks and city commercial banks for all variables, excluding that joint-equity commercial banks have the lowest capital adequacy and highest ROE. But they display the highest standard deviation for ROE and share of customer deposits in total assets. City commercial banks, which are smaller than the other banks, have the highest loan growth (5.64%), as well as general risk reserves ratio, net profit per employee, and lead in terms of liquidity. But City commercial banks have the lowest ROE with a small standard deviation and insured funding share. Standard

deviations for city commercial banks' loan growth, capital adequacy, general risk reserves ratio, net profit per employee, and cash-to-assets, are the highest among all bank groups.

Comparing global systemically important banks (G-SIBs) with other banks, G-SIBs have, on average, lower loan growth (3.2%), general risk reserve ratio, net profit per employee, and poorer liquidity. G-SIBs have higher average capital adequacy, ROE, and share of customer deposits in total assets and bank size. Tn terms of standard deviation, G-SIBs shows more stability for every variable excluding bank size listed in Table 3.4.

Looking at graph 3.2 for the 14 banks, we generally observe a downward trend and, as well as seasonal patterns, and substantial outliers for loan growth during the global financial crisis. An exception is Ping An Bank Co., Ltd., which shows a spike in a different time, 2011Q3. The sharp loan growth in these years is associated with the government oriented economic stimulus package after financial crisis (Liu et al., 2018). This state intervention can be seen as an example of a planned or bureaucratic pattern, that does not respond to short term economic variables. Generally descriptive analysis, shows a lot of movement in other variables, that do not seem to be related to loan growth. Examples for this are big movements in capital adequacy and big jumps in general risk reserve between 2012 and 2013. In 2012, the Ministry of Finance of the P.R. China increased general risk reserve balance requirements from 1% to 1.5% of the ending balance of risky assets from July 2012 (it should not be lower than 1% between July 2005 and June 2012.), which is phased in over 5 years for financial institutions. This is why the general risk reserve proportion has jumps. We include a dummy for this jump in general risk reserve but it has not significant effect on loan growth. There are strong seasonality in management variable (net profit margin per employee) and earning variable (return on equity) and small seasonality in other variables. Cash-to-assets ratio moves around quite a lot. This raises a question about how much influence the economic variables have on loan growth. So looking at the graphs, we see a fairly simple deterministic pattern in loan growth despite a large variations in the economic variables that are would expect to influence loan growth. This suggests that the planning process may be the main influence. These are based on graphs, we need to look at the regressions.

Table 3.5 illustrates the correlation matrix between variables from 2008Q1 to 2018Q4. All the correlations are smaller than 0.5 excluding: the correlations of general risk reserve ratio and customer deposits to assets, and of ROE and net profits per employee.

Table 3.3 CAMEL variables, mean.

crossid and groups of banks	Dependent variable	C	A	M	E	L		Bank size	
	NLG	**ETA**	**GRRTTL**	**NPTEMP**	**ROE**	**CTA**	**DCTTA**	**BS**	**TA (trillion CNY)**
Pooled 14 listed banks	0.0431	0.0630	0.0177	457221	0.1099	0.0708	0.6823	0.0714	5.52
Individual banks									
1	0.0307	0.0686	0.0165	341439	0.1198	0.0566	0.7814	0.2469	18.50
2	0.0329	0.0697	0.0153	368932	0.1233	0.0339	0.7948	0.1999	15.16
3	0.0325	0.0710	0.0153	321931	0.0989	0.0797	0.7272	0.1837	13.83
4	0.0340	0.0655	0.0162	400696	0.0999	0.0423	0.6699	0.0754	5.83
5	0.0524	0.0546	0.0167	356767	0.1004	0.0836	0.6906	0.0215	1.81
6	0.0437	0.0556	0.0164	577362	0.1202	0.0605	0.6633	0.0448	3.63
7	0.0384	0.0513	0.0171	295774	0.0957	0.0874	0.6759	0.0204	1.59
8	0.0399	0.0600	0.0202	477359	0.1161	0.0571	0.6526	0.0416	3.41
9	0.0408	0.0620	0.0164	500569	0.1285	0.0874	0.7196	0.0501	3.97
10	0.0463	0.0547	0.0201	531386	0.1269	0.0861	0.5470	0.0438	3.66
11	0.0430	0.0677	0.0173	485725	0.0962	0.0741	0.7222	0.0439	3.55
12	0.0482	0.0669	0.0205	758575	0.1039	0.1038	0.6557	0.0161	1.33
13	0.0648	0.0715	0.0240	550359	0.0974	0.0335	0.6374	0.0062	0.55
14	0.0563	0.0635	0.0152	434219	0.1111	0.1059	0.6141	0.0058	0.51
Chinese groups of banks									
SOCBs: 4 large state-owned commercial banks	0.0325	0.0687	0.0158	358249	0.1105	0.0531	0.7433	0.1765	13.33
JECBs: 7 joint-equity commercial banks	0.0435	0.0580	0.0177	460706	0.1120	0.0766	0.6673	0.0380	3.09
CCBs: 3 city commercial banks	0.0564	0.0673	0.0199	581051	0.1041	0.0811	0.6357	0.0094	0.80
Global groups of banks									
G-SIBs: 3 global systemically important banks	0.0320	0.0698	0.0157	344101	0.1140	0.0567	0.7678	0.2102	15.83
G-SUIBs: 11 other banks	0.0462	0.0612	0.0182	488072	0.1088	0.0747	0.6589	0.0336	2.71

Table 3.4 CAMEL variables, standard deviation.

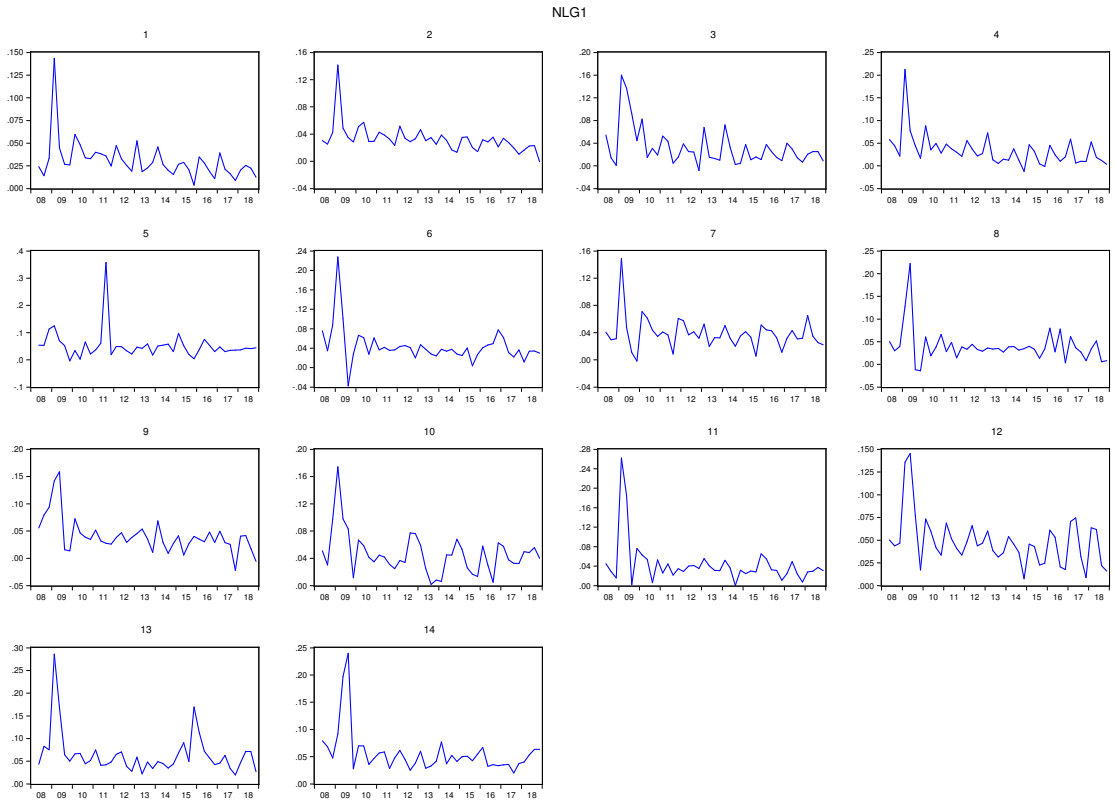
crossid and groups of banks	Dependent variable	C	A	M	E	L		Bank size	
	NLG	**ETA**	**GRRTTL**	**NPTEMP**	**ROE**	**CTA**	**DCTTA**	**BS**	**TA (trillion CNY)**
Pooled 14 listed banks	0.0367	0.0126	0.0063	264803	0.0502	0.0393	0.0956	0.0762	6.23
Individual banks									
1	0.0214	0.0099	0.0035	170377	0.0532	0.0135	0.0355	0.0214	5.69
2	0.0205	0.0079	0.0037	178915	0.0516	0.0101	0.0385	0.0113	5.10
3	0.0341	0.0081	0.0039	160580	0.0420	0.0204	0.0214	0.0140	4.37
4	0.0357	0.0095	0.0055	199766	0.0452	0.0132	0.0622	0.0016	2.23
5	0.0540	0.0124	0.0040	189507	0.0488	0.0268	0.0615	0.0058	1.03
6	0.0366	0.0128	0.0060	294477	0.0608	0.0258	0.0995	0.0062	1.73
7	0.0233	0.0143	0.0034	160776	0.0473	0.0371	0.0604	0.0008	0.65
8	0.0375	0.0069	0.0076	230781	0.0512	0.0344	0.0951	0.0071	1.75
9	0.0323	0.0097	0.0045	250117	0.0562	0.0204	0.0571	0.0040	1.72
10	0.0308	0.0077	0.0084	258767	0.0559	0.0331	0.0704	0.0099	1.99
11	0.0444	0.0070	0.0063	219298	0.0431	0.0297	0.0879	0.0063	1.69
12	0.0275	0.0071	0.0064	420828	0.0423	0.0316	0.0949	0.0030	0.70
13	0.0463	0.0180	0.0084	255475	0.0399	0.0114	0.0305	0.0026	0.40
14	0.0400	0.0112	0.0065	211246	0.0457	0.0777	0.0704	0.0020	0.33
Chinese groups of banks									
SOCBs: 4 large state-owned commercial banks	0.0285	0.0091	0.0042	178953	0.0491	0.0228	0.0647	0.0645	6.48
JECBs: 7 joint-equity commercial banks	0.0380	0.0116	0.0061	248202	0.0534	0.0321	0.0946	0.0127	1.79
CCBs: 3 city commercial banks	0.0390	0.0133	0.0080	335179	0.0428	0.0591	0.0720	0.0054	0.63
Global groups of banks									
G-SIBs: 3 global systemically important banks	0.0259	0.0087	0.0037	169924	0.0500	0.0241	0.0437	0.0313	5.41
G-SUIBs: 11 other banks	0.0386	0.0067	276975	0.0501	0.0416	0.0925	0.0874	0.0210	2.14

Note: TA represents total assets.

Table 3.5 Correlation coefficients, pooled data for 14 banks.

	NLG	ETA	GRRTTL	NPTEMP	ROE	CTA	DCTTA	BS
NLG	1	-0.15	-0.23	-0.28	-0.29	0.04	-0.10	-0.18
ETA	-0.15	1	0.26	0.16	-0.19	-0.20	-0.05	0.32
GRRTTL	-0.23	0.26	1	0.38	-0.11	-0.33	-0.64	-0.18
NPTEMP	-0.28	0.16	0.38	1	0.63	-0.01	-0.33	-0.21
ROE	-0.29	-0.19	-0.11	**0.63**	1	0.09	0.13	0.07
CTA	0.04	-0.20	-0.33	-0.01	0.09	1	0.08	-0.22
DCTTA	0.10	-0.05	**-0.64**	-0.33	0.13	0.08	1	0.49
BS	-0.18	0.32	-0.18	-0.21	0.07	-0.22	0.49	1

Fig. 3.2 NLG: Loan growth at quarterly rate.



Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

3.5 Research methods and results

The objective of our analysis is to determine the extent to which the loan growth of Chinese banks reflects government intervention or market forces as reflected in the bank specific determinants discussed above.

As noted above the government intervenes in various ways including credit quotas, monetary policy, window guidance, etc. Thus it is difficult to measure government intervention. Therefore, many researchers simply attributed loans growth to Chinese government decisions. However, we think that even though the government lending policies make difference, the banking institutions can have some freedom to make decisions according to market rules. Even though the state sometimes intervenes through specific lending decisions for banks, it typically gives lending directions macroeconomically and does not intend to control banks' lending operations in detail. We use some variables that we will label *bureaucratic variables* to represent possible government actions plus some bank specific variables that we will label *economic variables*. We will then ask about the respective contribution of these two sets of variables. The bureaucratic variables include deterministic elements like trends, seasonal terms and dummies representing state directives during the crisis plus a lagged dependent variable reflecting inertia or slow adjustment. The economic variables include bank-specific economic factors that, in a market system, one would expect to influence loan growth. Economic variables considered follow the CAMEL approach outlined above.In choosing our model we will answer: Which variable should be included in the final model specifications; how many lags should be included; and how much heterogeneity is there in the banks and groups of banks?

Our baseline model has a vector of independent variables, x_i, which are either current or lagged one period to reduce the endogeneity, plus the lagged dependent variable to allow for any slow adjustment. For the homogeneous slope model we employ fixed-effects within estimators. The homogeneous slope current economic variables model is

$$\begin{aligned} NLG_{it} = {} & \alpha_i + \beta' x_{i,t} + \delta' D9Q(q) + \rho DB511Q3 \\ & + \sigma' @SEAS(q) + \phi @TREND + \gamma NLG_{i,t-1} + v_{it}. \end{aligned} \tag{3.5.1}$$

NLG_{it} is the dependent variable, loan growth; x_{it} gives a vector of economic variables including equity to assets (ETA), general risk reserves to total assets (GRRTTA), net profits per employee (NPTEMP), ROE, cash to assets (CTA), customer deposits to total assets (DCTTA), and bank size (BS); $D9Q(q), q = 1,2,3$ capture outliers in loan growth in 2009Q1, 2009Q2, and 2009Q3, respectively; $DB511Q3$ captures the outlier in loan growth of Ping An Bank Co., Ltd. in 2011Q3; $@SEAS(q), q = 1,2,3$ capture seasonal effects; $@TREND$ is a trend term; α_i is a vector of bank specific constants v_{it} is an error term. β' is a vector of coefficient of variables $x_{i,t}$, δ' of $D9Q(q)$, ρ of $DB511Q3$; σ' of $@SEAS(q)$, ϕ of $@TREND$, and γ of $NLG_{i,t-1}$.

The homogeneous slope lagged economic variables model is

$$\begin{aligned} NLG_{it} = \alpha_i + \beta^{'} x_{i,t-1} + \delta^{'} D9Q(q) + \rho DB511Q3 \\ + \sigma^{'} @SEAS(q) + \phi @TREND + \gamma NLG_{i,t-1} + v_{it}. \end{aligned} \tag{3.5.2}$$

The heterogeneous slope lagged economic variables model involves estimating the model for each individual bank:

$$\begin{aligned} NLG_{it} = \eta_i + \beta_i^{'} x_{i,t-1} + + \delta_i^{'} D9Q(i) + \rho_i DB511Q3 \\ + \sigma_i^{'} @SEAS(i) + \phi_i @TREND + \gamma_i NLG_{i,t-1} + \mu_{it}. \end{aligned} \tag{3.5.3}$$

3.5.1 Pooled fixed effects panel regressions

3.5.1.1 Homogeneous model specification

We explain loan growth with the variables suggested by the CAMEL approach as well as bank size and bureaucratic variables. We start using a general specification of 7 variables, which we subsequently reduce to 4 economic variables following a stepwise selection procedure and economic analysis. Models are re-evaluated throughout the selection procedure using information criteria, tests for omitted variables, and economic judgment.

Table 3.6 shows fixed effects panel estimations. The general fixed effect specification (GEQ1) includes all variables illustrated by the homogeneous slop current economic variables model (3.5.1): 7 economic variables plus 3 seasonals, a trend, 3 dummies and a lagged dependent variable. The specific specification (SEQ1) gives a specification obtained after stepwise dropping least significant variables until all variables are significant. Both information criteria, Akaike info criterion (AIC) and Schwarz criterion (BIC), suggest the specific specification SEQ1 rather the general specification GEQ1.

There may be reverse causality from loan growth of banks onto economic variables. To address this endogeneity, we used lagged values of economic variables. Our dynamic general model (3.5.2) therefore contains the 7 economic variables lagged by one quarter plus 3 seasonals, a trend, 3 dummies and a lagged dependent variable. The specific specification, SEQ2a, gives a specification obtained after stepwise dropping least significant variables until all variables are significant excluding lagged loan growth and the constant.[9] Comparing model specifications, SEQ1 and SEQ2, AIC prefers the homogeneous lagged economic variables model and BIC the current economic economic variables one. Once we drop the

[9] Although lagged loan growth is insignificant in the lagged economic variables model. We retain it, so we can compare between specifications.

insignificant lagged loan growth from the lagged economic variables specific model (SEQ2a), BIC turns to suggest the lagged economic variables model.

Whilst the preceding variable selection was purely based on econometric criteria, we select homogeneous lagged economic variables specification, SEQ2b, as baseline specification, by applying further analytic judgment: Net profit margin per employee on loans growth is dropped despite its significance, given an effect size that is approximately zero. We are further interested in evaluating the effects of liquidity on loans growth and hence include cash to assets ratio in the specification SEQ2b although it is insignificant.

3.5.1.2 Results

Based on homogeneous lagged economic variables specifications, bank lending is significantly affected by a combination of economic and bureaucratic variables. Strikingly, the combined impact of economic variables out-sizes that of deterministic factors by roughly a factor three. Effects of equity and risk reserves ratios are particularly strong and positive as expected. In the homogeneous current economic variables specifications economic factors turn largely insignificant, apart from ETA, which has a relatively large effect on bank lending, albeit only weakly significant.

Table 3.6 General to specific estimations, coefficients. Dependent variable: NLG; Method: Fixed Effects Panel Least Squares.

Regressor	GEQ1	SEQ1	Regressor	GEQ2	SEQ2a	SEQ2b
ETA	**0.223***		ETA(-1)	**0.547*****	**0.543*****	**0.510*****
GRRTTL	-0.344		GRRTTL(-1)	**0.733*****	**0.687*****	**0.588***
NPTEMP	-6.57E-09		NPTEMP(-1)	**-1.88E-08*****	**-2.21E-08*****	
ROE	0.028		ROE(-1)	**0.145****	**0.123*****	**0.131***
CTA	-0.051		CTA(-1)	0.036		0.035
DCTTA	0.016		DCTTA(-1)	0.014		
BS	0.140		BS(-1)	0.001		
C	0.011	**0.038*****	C	-0.028	-0.007	-0.020
@SEAS(1)	**0.019****	**0.019*****	@SEAS(1)	**0.017*****	**0.018*****	**0.015*****
@SEAS(2)	**0.010***	**0.008*****	@SEAS(2)	**0.015****	**0.011*****	**0.021*****
@SEAS(3)	0.000		@SEAS(3)	0.003		**0.006***
@TREND	-0.0002	**-0.0004*****	@TREND	**-0.0005****	**-0.0006*****	**-0.0006*****
D9Q1	**0.113*****	**0.112*****	D9Q1	**0.108*****	**0.107*****	**0.110*****
D9Q2	**0.070*****	**0.068*****	D9Q2	**0.073*****	**0.073*****	**0.072*****
D9Q3	0.009		D9Q3	**0.013***	**0.013***	**0.014****
DB511Q3	**0.319*****	**0.320*****	DB511Q3	**0.322*****	**0.324*****	**0.320*****
NLG(-1)	0.024	**0.056***	NLG(-1)	0.037	0.036	0.037
R^2	0.65	0.65	R^2	0.67	0.66	0.66
MLL	1416.40	1411.22	MLL	1426.33	1424.76	1423.31
AIC	-4.716	-4.729	AIC	-4.749	-4.758	-4.753
BIC	-4.492	-4.572	BIC	-4.526	-4.564	-4.559
DW	1.94	1.99	DW	1.94	1.95	1.94

Note 1: GE indicates the general model. SE indicates the specific model. First block current economic variables and second block lagged.
Note 2: * denotes significance at the 10% level, ** at the 5% level, and * at the 1% level.

3.5.2 Heterogeneity in the banks and groups of banks

3.5.2.1 Sample selection and model specification

Preceding results give fixed-effects estimates that are pooled for all 14 banks. This allows to control for unobserved heterogeneity in intercepts, whilst taking advantage of the full sample of observations available. But large degree of heterogeneity across banks can result in biased pooled estimates. We therefore estimate the heterogeneity across estimates explicitly in models for individual banks (see Table 3.8) on the basis of the baseline specification SEQ2b. We further cluster banks with similar characteristics groups, which gives more efficient estimates whilst avoiding some of the bias present in the pooled panels (see Table

3.8). Table B.1 in the appendix shows diagnostic tests for the baseline general specifications, which suggests these specifications for the individual banks are reliable.

Banks are clustered along two dimensions: Chinese groups distinguished mainly by the government (large state-owned commercial banks (SOCBs), joint-equity commercial banks (JSCBs), and city commercial banks (CCBs)) and global groups by systemic importance (global systemically important banks (G-SIBs), and others (G-SUIBs)). The pooled general model uses the usual standard errors. If White heteroskedasticity robust standard errors are used, they are larger and only ETA(-1) is significant at the 10% level.

We compare models based on sums of information criteria for individual banks and bank groups. Given the loss of efficiency as we reduce sample sizes, we employ further stepwise elimination of insignificant variables, which further reduces parameters and retains comparatively high degrees of freedom (see Table 3.9). Results suggested in the model selection stage are ambiguous (see Table 3.7): For the baseline specific models, the AIC and BIC both suggest individual bank as samples. For baseline general models, BIC prefers samples clustered by global groups, whilst AIC again indicates individual banks. The information criteria reflect fit as measured by Log likelihood and parsimony as reflected in the number of parameters. BIC penalizes the number of parameters more and hence reflects the difference in sample size to a greater extend. Moving from baseline general to specific models for individual banks means that there is a large reduction in the number of parameters from 183 to 83, for the Chinese bank groups from 53 to 39, and for the global groups from 40 to 32. Given this large difference in parameters applied to relatively small samples, we tend to err on the side of model parsimony and regard the choice indicated by BIC as more reliable.

Table 3.7 AIC and BIC

	Baseline general specifications				**Baseline specific specifications**			
	MLL	**k**	**BIC**	**AIC**	**MLL**	**k**	**BIC**	**AIC**
Fixed effects panel of 14 banks	1423.91	27	1337.82	1396.91	1423.91	27	1337.82	1396.91
Individual banks	1775.03	183	1191.56	**1592.03**	1760.35	83	**1495.72**	**1677.35**
Chinese groups	1500.77	53	1331.79	1447.77	1520.48	39	1396.13	1481.48
Global groups	1468.16	40	**1340.62**	1428.16	1491.47	32	1389.45	1459.47

3.5.2.2 Results

Given the further reduction in considered covariates, we report results for baseline general and specific models separately. Results are given in tables 3.8 and 3.9, respectively.

3.5.2.2.1 Baseline general models Table 3.8 gives results for regressions on individual banks and bank groups using baseline general specifications. Results are similar to general specifications for pooled estimates. Most significant effects are through deterministic terms, particularly the first seasonal dummy, SEAS(1), and the first crisis dummy, D9Q1, which indicates a significant degree of state intervention affecting lending growth. This notwithstanding we find significant effects of bank specific market factors for clustered bank groups. The state intervention could be explained by the 4-trillion-yuan stimulus package adopted by the Chinese government. In September 2008, after the outbreak of the global financial crisis, China's economic growth slowed down rapidly, with negative exports growth and a large number of migrant workers returning home. The economy was at risk of a hard landing. In response to this crisis, the State Council approved a plan to invest 4 trillion yuan in infrastructure and social welfare by the end of 2010. The Chinese government launched ten measures, for example, providing funds for infrastructure projects and housing developments, in November 2008 to further expand domestic demand and promote steady and rapid economic growth. According to preliminary calculations, the implementation of these ten measures would require an investment of about 4 trillion yuan by the end of 2010.

Accordingly, market factors, particularly equity ratios and risk buffers, significantly affect joint-equity commercial banks, which are partly privatised, as well as systemically unimportant banks, which excludes the three largest state-owned commercial banks. To find large state-owned commercial banks being less exposed to market forces is unsurprising, given that they benefit from being too big to fail, and are more exposed to policy decisions rather than market factors.

In terms of relative contribution of market and bureaucratic variables, the former tend to be larger in size but are generally less significant, particularly for estimates of individual banks. Here, a lack of efficiency given the lack of available data appears decisive. But given the more efficient estimates for bank groups, we do find significant evidence for the impact of market dynamics. Where significant, the effect of market factors again outsizes that of bureaucratic variables by a large margin.

3.5.2.2.2 Baseline specific models Table 3.9 applies a further stepwise elimination of insignificant variables as outlined before. This tackles the problem of efficiency that is present for individual bank estimates and requires a more parsimonious approach. We apply the elimination to both, market and bureaucratic variables. Results nor indicate a more significant impact of market variables, which is generally in line with previous results. Most privately capitalised banks increase lending given higher equity ratios and risk-buffers, whilst some cases of state-owned commercial banks suggest the opposite. In particular for Bank of

Communications, there is a significant negative effect of risk buffers and return on equity on lending behaviour, which suggests lending decisions driven by policy considerations not commercial factors.

Findings for bank groups validate previous results. Furthermore the coefficient on ETA(-1) for city commercial banks is now significant, which reiterates the importance of market factors for banks which has a relatively diverse ownership structure.

3.6 Conclusion

We study Chinese bank lending for a panel of 14 Chinese banks over the decade following the global financial crisis. In doing so, we investigate the degree to which bank lending is driven by economic factors or a set of bureaucratic, deterministic variables. We find significant effects on bank lending through both economic and bureaucratic variables, based on pooled fixed-effects estimates. The impact of economic factors is less significant in heterogeneous panels. This suggests significant exposure of joint-equity banks and global systemically unimportant banks to market forces. Bank lending through systemically relevant and state-owned commercial Chinese banks hence appears to be rather driven by policy and "too-big-to-fail" effects than commercial considerations.

These results suggest that, whilst there remains a large degree of state influence on Chinese banks, there is evidence for market exposure even at a time of unprecedented state interventions following the global financial crisis. Using new data that allows exploring the heterogeneity of the Chinese banking system, we thus find crucial evidence for the development of the Chinese banking system into a market economy. Further promising research could attempt to compare the results on bank specific factors with that for US banks, to compare the degree to which market factors affected bank lending in a developed market economy post 2008. It will also be interesting to see if the pattern of bank lending remains the same in the future if Chinese growth is slower.

This research is a starting-point towards evaluating Chinese financial development. Following chapters investigate this from a macroeconomic perspective, analysing how the interaction of key macro-economic aggregates resembles aggregate goods and money supply and demand relationships.

Table 3.8 Baseline general Specifications, coefficients. Dependent variable: NLG; Method: Panel Least Squares.

Regressors	ETA(-1)	GRRTTL(-1)	ROE(-1)	CTA(-1)	C	@SEAS(1)	@SEAS(2)	@SEAS(3)	@TREND	D9Q1	D9Q2	D9Q3	NLG(-1)	DB511Q3	R^2	MLL	DW
Fixed Effects Panel:																	
14 banks	**0.510*****	**0.588***	**0.131****	0.035	-0.020	**0.015*****	**0.021*****	**0.006***	**-0.001*****	**0.110*****	**0.072*****	**0.014****	**0.320*****	0.037	0.66	1423.91	1.94
Individual banks (crossid, heterogeneous panel estimation):																	
1	-0.598	-0.042	0.029	-0.021	0.058	**0.021*****	0.014	0.004	0.000	**0.098*****	0.004	-0.005	0.028		0.91	153.58	2.04
2	-0.083	0.345	0.067	0.128	0.016	**0.016*****	0.018	0.007	-0.001	**0.086*****	-0.008	0.000	0.120		0.92	155.46	1.99
3	-0.300	0.479	0.248	-0.143	0.002	**0.032*****	0.029	0.013	0.000	**0.126*****	**0.100*****	**0.058*****	0.181		0.89	128.98	2.54
4	-0.324	**-2.936**	-0.350	-0.300	0.152	**0.048*****	-0.005	0.002	0.000	**0.161*****	**0.082****	0.017	**-0.338***		0.92	133.27	2.24
5	**2.714****	**4.048***	0.365	0.007	**-0.166***	-0.004	0.041	0.027	**-0.003*****	**0.150*****	**0.054***	0.030	**0.316*****	-0.024	0.90	110.36	1.61
6	-1.096	1.583	0.049	0.080	0.060	-0.001	0.008	-0.013	0.000	**0.152*****	0.003	**-0.094*****	0.182		0.87	123.14	1.98
7	0.926	2.696	0.195	-0.119	-0.037	0.013	0.025	0.002	**-0.002***	**0.098*****	0.009	-0.015	-0.067		0.75	127.57	2.24
8	0.825	1.281	-0.157	0.134	-0.008	**0.019***	-0.005	-0.002	-0.001	**0.077*****	**0.204*****	0.008	-0.155		0.83	116.15	2.16
9	1.743	1.832	0.114	-0.086	-0.069	**0.021****	0.018	0.018	**-0.002*****	**0.062*****	**0.113*****	-0.025	0.074		0.83	122.04	2.00
10	1.270	0.636	**0.545****	**0.578*****	**-0.194****	-0.018	**0.048*****	0.010	0.001	**0.083*****	**0.058****	**0.068*****	0.222		0.78	118.05	1.69
11	-0.151	0.611	-0.194	-0.018	0.082	0.008	-0.011	-0.017	-0.001	**0.211*****	**0.146*****	-0.028	-0.050		0.90	120.08	1.75
12	0.619	-1.095	0.221	0.029	-0.033	**0.036*****	**0.050****	0.017	0.000	**0.058*****	**0.080*****	**0.037****	-0.010		0.90	138.75	1.62
13	0.508	1.766	-0.236	0.249	-0.003	0.005	-0.020	-0.019	-0.001	**0.201*****	0.032	-0.019	0.309		0.76	99.13	1.98
14	0.427	0.952	0.044	-0.038	0.021	**0.014***	0.009	-0.004	-0.001	0.019	**0.143*****	**0.206*****	-0.065		0.92	128.46	1.24
Mean	0.463	0.868	0.067	0.034	-0.009	0.015	0.016	0.003	-0.001	0.113	0.073	0.017	0.053	-0.024			
Std. Dev.	1.006	1.654	0.245	0.207	0.092	0.017	0.022	0.013	0.001	0.056	0.064	0.068	0.184				
Groups of banks (Fixed Effects):																	
SOCBs	-0.078	-0.454	0.038	**0.163****	0.017	**0.030*****	0.013	0.005	0.000	**0.106*****	**0.024****	**0.015***	0.123		0.80	492.32	2.02
JSCBs	**0.869*****	**0.885***	**0.139****	0.053	**-0.033***	**0.007***	**0.019*****	0.005	**-0.001*****	**0.121*****	**0.091*****	-0.009	**0.320*****	-0.032	0.70	719.04	2.01
CCBs	0.410	0.951	-0.069	0.006	0.011	**0.021****	0.006	-0.004	-0.001	**0.094*****	**0.094*****	**0.068*****	0.101		0.62	289.40	1.84
G-SIBs	0.293	0.500	0.050	**0.213****	-0.022	**0.026*****	0.010	0.004	**-0.001***	**0.088*****	0.011	0.014	**0.262*****		0.80	381.31	1.91
G-SUIBs	**0.535*****	**0.680***	**0.130****	0.033	-0.018	**0.013*****	**0.020*****	0.005	**-0.001*****	**0.115*****	**0.085*****	0.013	**0.321*****	0.019	0.65	1086.85	1.95

Note: * denotes significance at the 10% level, ** at the 5% level, and * at the 1% level.

Table 3.9 Baseline specific specifications, coefficients. Dependent variable: NLG; Method: Panel Least Squares.

Regressors	ETA(-1)	GRRTTL(-1)	ROE(-1)	CTA(-1)	C	@SEAS(1)	@SEAS(2)	@SEAS(3)	@TREND	D9Q1	D9Q2	D9Q3	NLG(-1)	DB511Q3	R^2	MLL	DW
Fixed Effects Panel:																	
14 banks	**0.510*****	**0.588***	**0.131****	0.035	-0.020	**0.015*****	**0.021*****	**0.006***	**-0.001*****	**0.110*****	**0.072*****	**0.014****	**0.320*****	0.037	0.66	1423.91	1.94
Individual banks (crossid):																	
1	**-0.685*****				**0.068*****	**0.021*****	**0.010*****			**0.097*****					0.90	155.01	1.92
2				**0.211***	**0.031*****	**0.015*****	**0.009*****		**-0.001*****	**0.088*****					0.89	154.80	1.77
3					**0.007***	**0.039*****				**0.113*****	**0.084*****	**0.045****	**0.287*****		0.87	125.85	2.63
4		**-2.545*****	**-0.181*****		**0.079*****	**0.044*****				**0.150*****	**0.028****				0.89	131.02	2.41
5		**4.640****				0.000			**-0.002****	**0.072*****				**0.317*****	0.86	106.98	1.87
6	**-0.588****				**0.068*****			**-0.013****		**0.159*****		**-0.097*****	**0.216*****		0.86	121.15	2.01
7	**1.107****	**4.082*****	**0.319*****	**-0.124***	**-0.073****		**0.031*****		**-0.002*****	**0.106*****					0.73	128.85	2.25
8			**-0.128***		**0.050*****	**0.022****				**0.080*****	**0.202*****		**-0.192****		0.81	112.96	2.06
9	**1.774**	**1.900*****			**-0.051****	**0.017*****			**-0.003*****	**0.073*****	**0.121*****				0.80	121.75	1.95
10	**1.747*****		**0.244*****	**0.478*****	**-0.132*****		**0.023****			**0.097*****	**0.072*****	**0.070*****			0.74	117.99	1.39
11					**0.038*****			**-0.015*****		**0.224*****	**0.147*****				0.88	119.89	1.90
12		**-0.780*****			**0.041*****	**0.038*****	**0.030*****	**0.008****		**0.069*****	**0.085*****	**0.037*****			0.88	140.29	1.75
13	**0.810***	**1.352***			-0.052					**0.197*****			**0.347*****		0.73	96.93	2.13
14	**0.609*****				0.006	**0.017*****					**0.144*****	**0.192*****			0.90	126.89	1.59
Mean	0.598	1.441	0.063	0.189	0.006	0.024	0.021	-0.007	-0.002	0.117	0.110	0.049	0.164	0.317			
Std. Dev.	0.957	2.766	0.255	0.302	0.067	0.014	0.011	0.013	0.001	0.050	0.054	0.103	0.244				
Groups of banks (Fixed Effects):																	
SOCBs				**0.191****	**0.014****	0.029***	**0.007****		0.000***	0.103***	0.018	**0.015***	**0.162****		0.79	490.97	2.05
JSCBs	**0.827*****	**0.966****	**0.116****		**-0.023***	**0.007***	**0.016*****		**-0.001*****	**0.120*****	**0.084*****			**0.323*****	0.69	734.84	2.06
CCBs	**0.331***				0.019	**0.020*****	**0.012****			**0.100*****	**0.110*****	**0.082*****			0.60	294.67	1.65
G-SIBs				**0.206*****	0.006	**0.027*****			**0.000*****	**0.090*****			**0.370*****		0.78	377.68	2.15
G-SUIBs	**0.435*****	**0.647***	**0.114***	0.033	-0.009	**0.013*****	**0.019*****	0.004	**-0.001*****	**0.116*****	**0.086*****	**0.014***		**0.321*****	0.65	1113.80	1.91

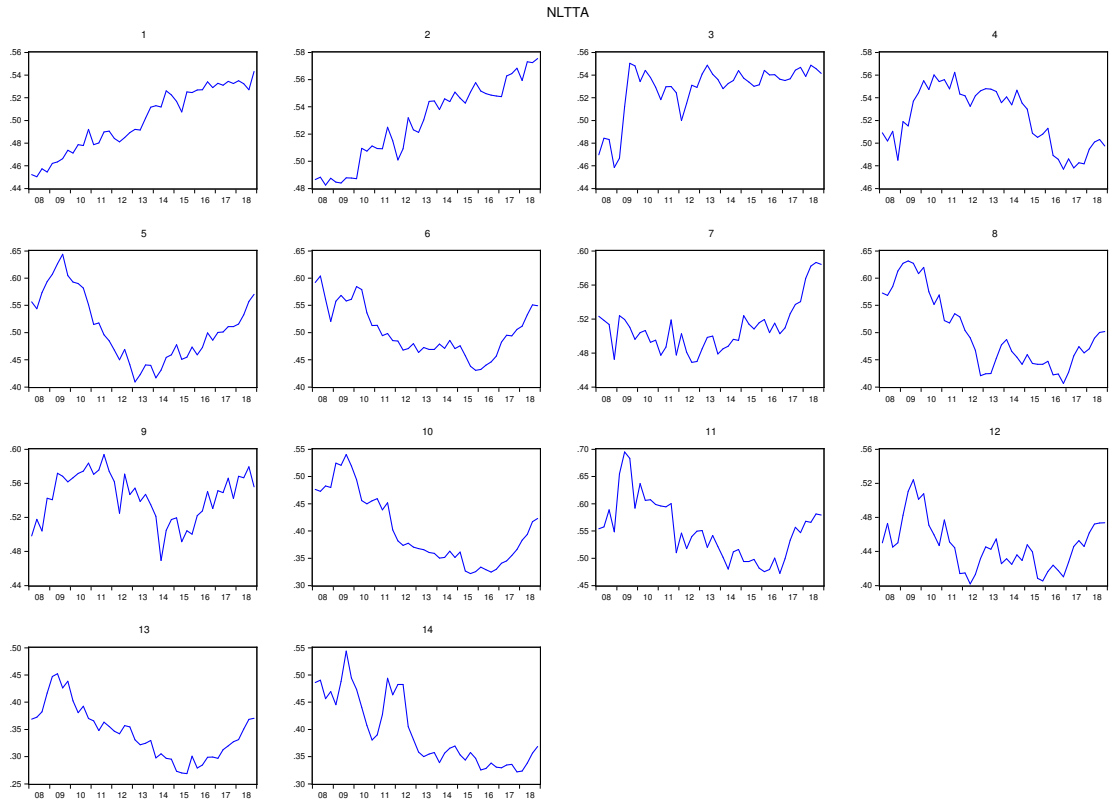
Note: * denotes significance at the 10% level, ** at the 5% level, and * at the 1% level.

Appendix B

Bank-specific Determinants of Loan Growth in China

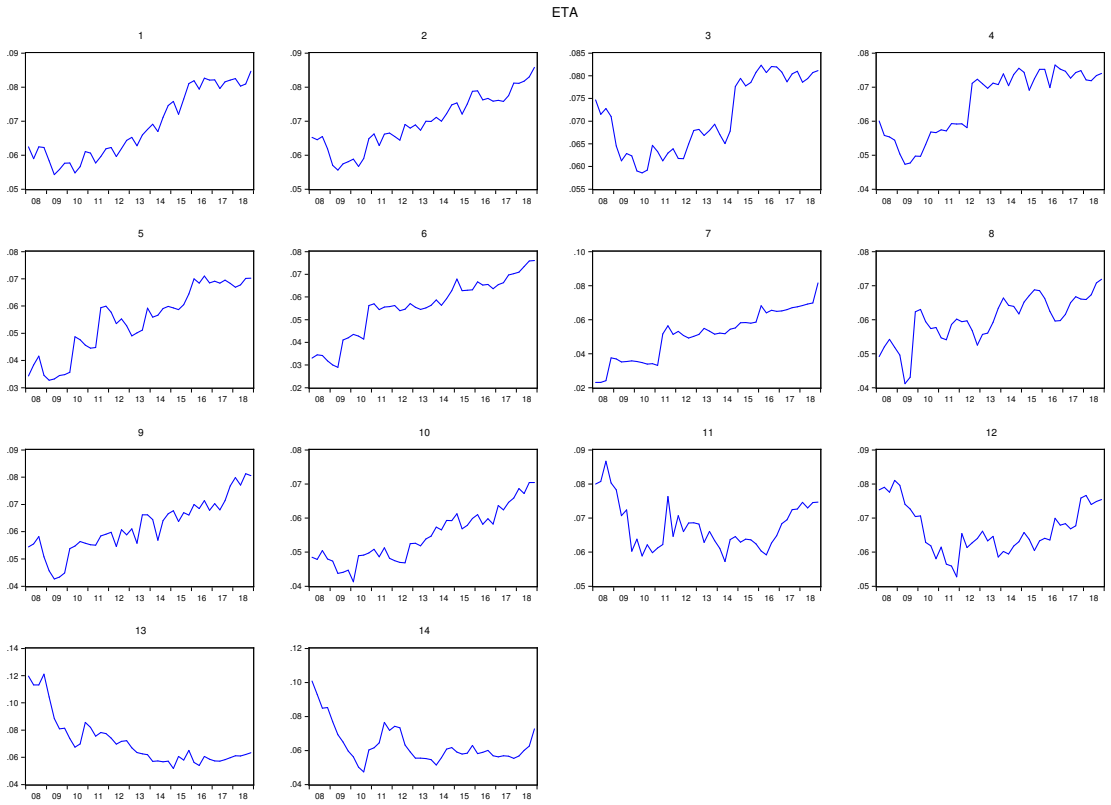
B.1 Patterns of bank-specific variables

Fig. B.1 NLTTA: Ratio of Net Loans and Receivables to Total Assets.



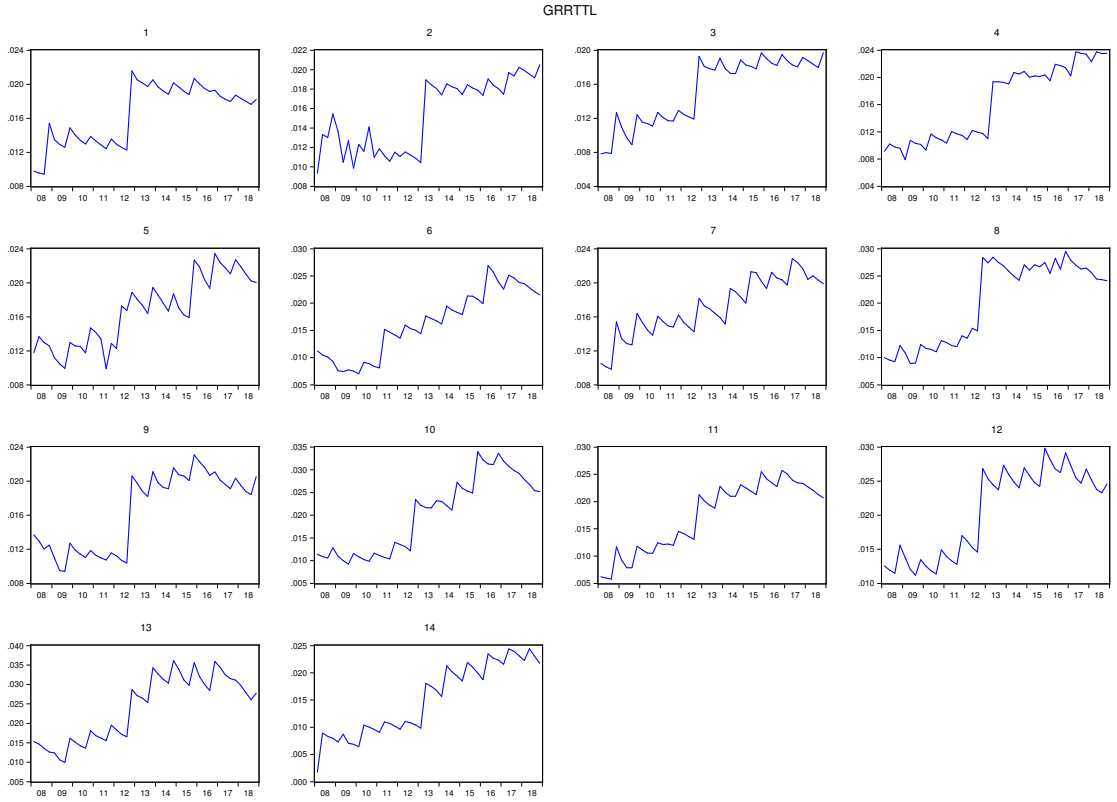
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.2 ETA: Ratio of Equity to Assets.



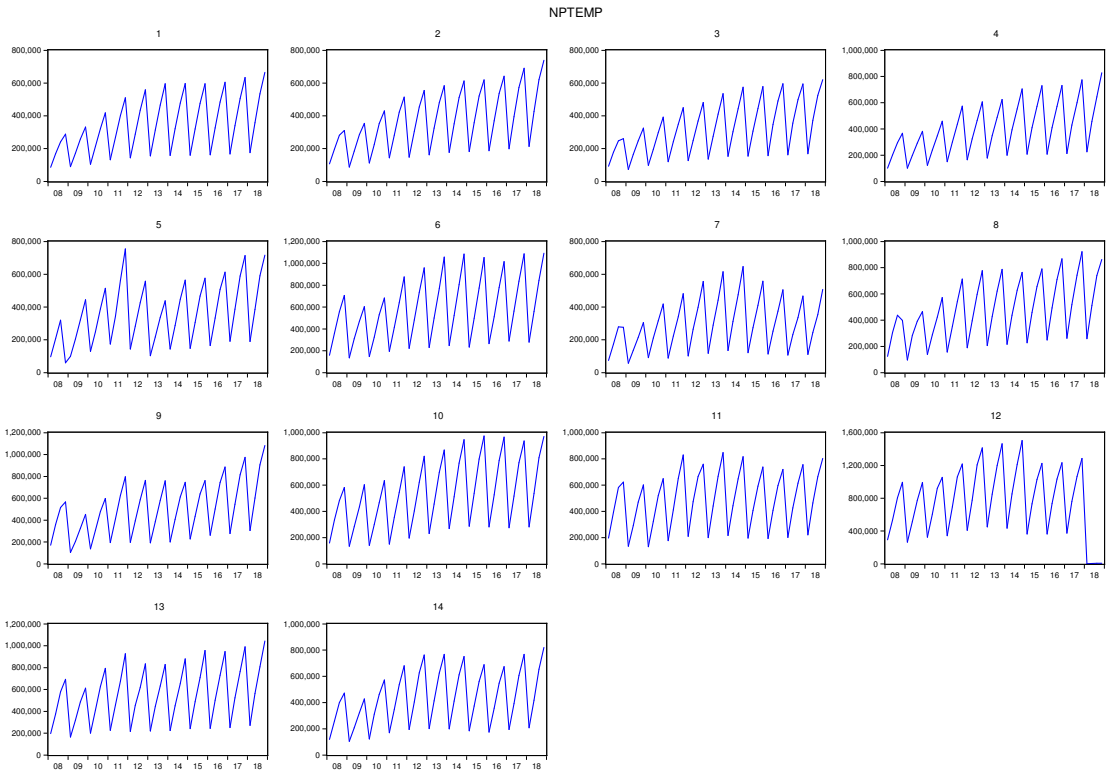
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.3 GRRTTL: Ratio of General Risk Reserves to sum of General Risk Reserves and Net Loans And Receivables.



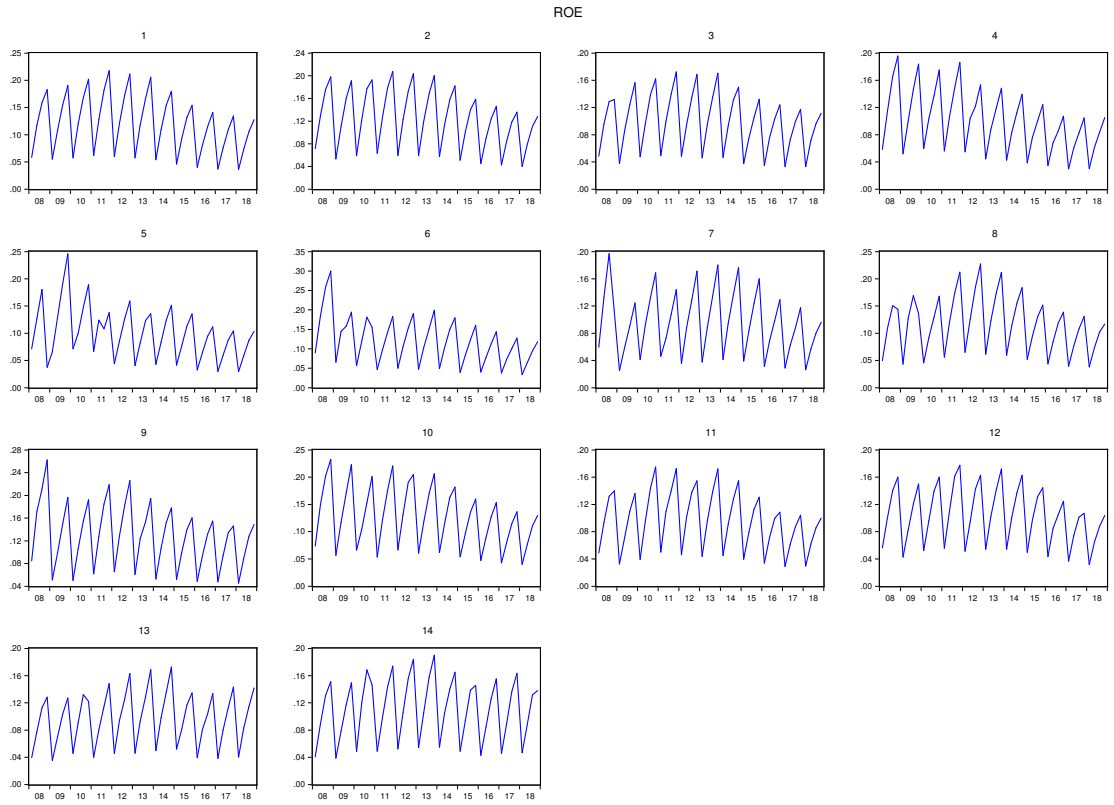
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.4 NPTEMP: Net Profits per Employee.



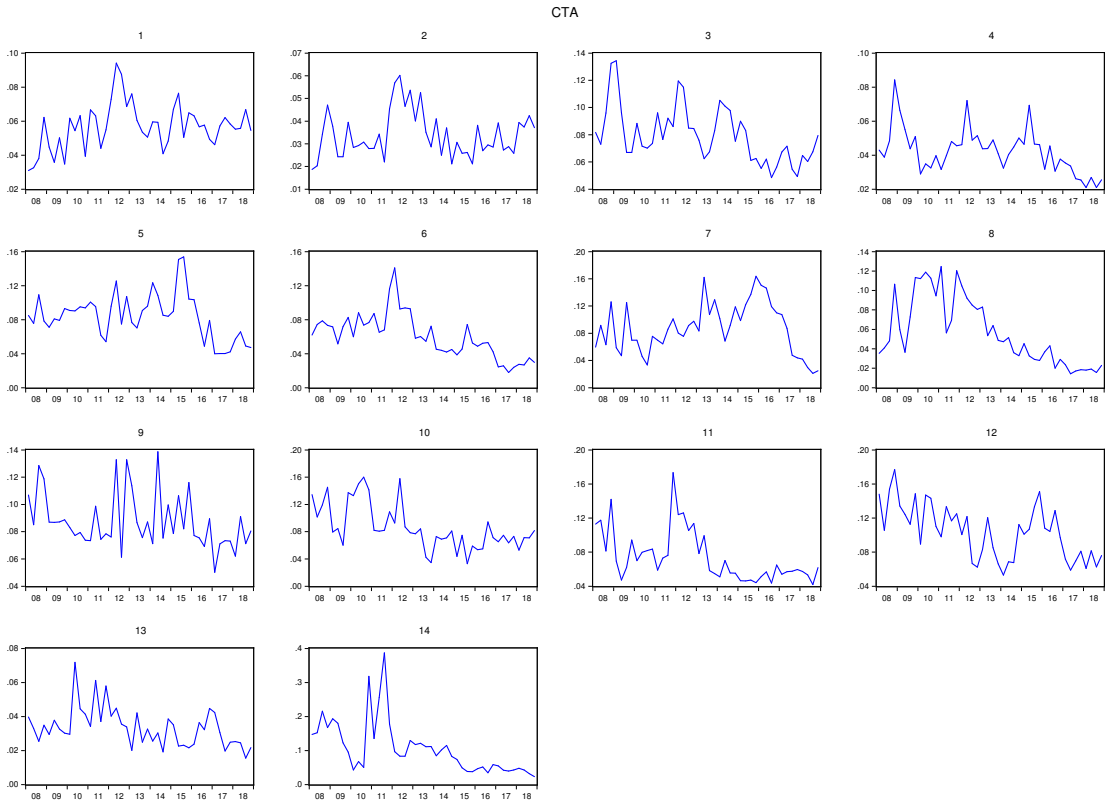
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.5 ROE: Return on Equity.



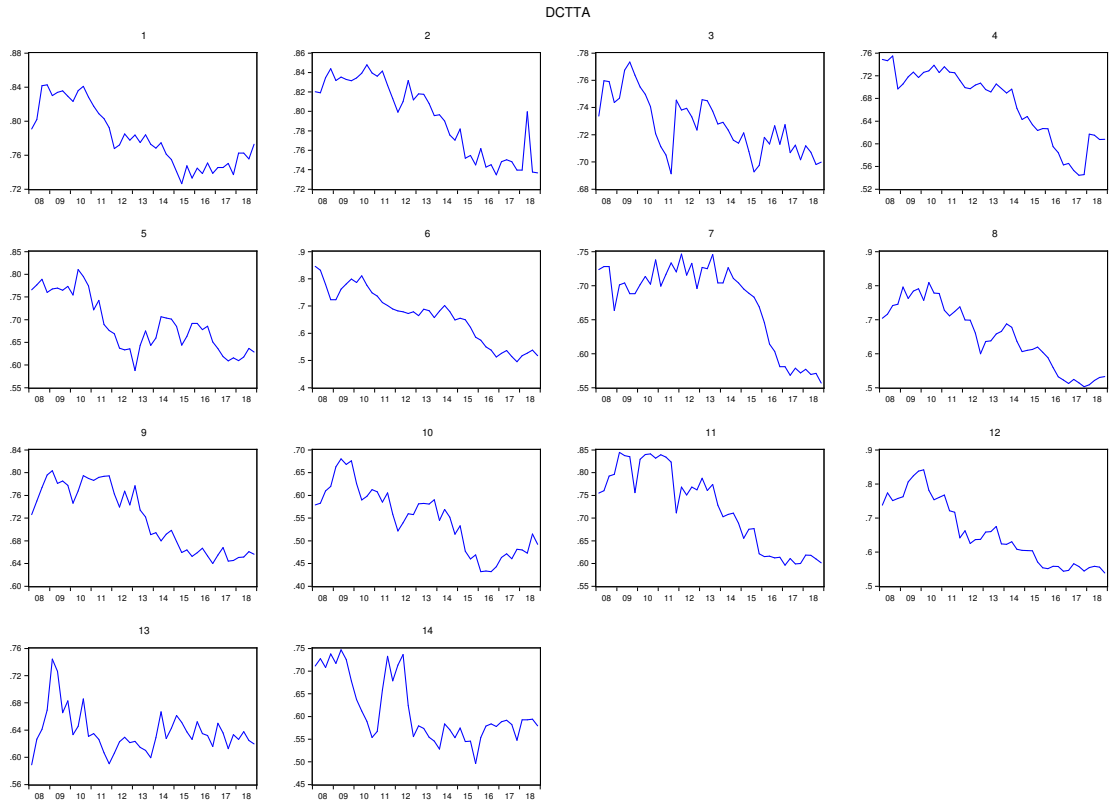
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.6 CTA: Ratio of Cash to Assets.



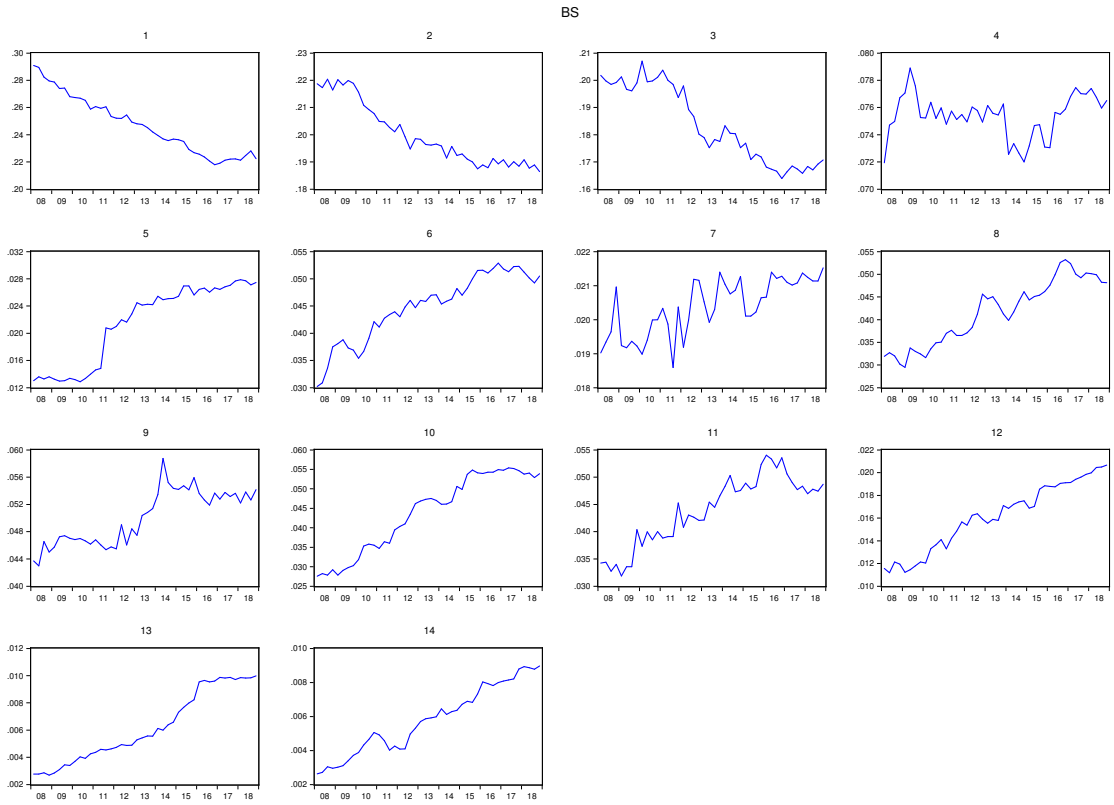
Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.7 DCTTA: Deposits Due To Customers to Total Assets.



Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

Fig. B.8 BS: Bank size.



Note: The number at top of each subgraph corresponds to the crossid of each bank listed in Table 3.1.

B.2 Diagnostics of baseline general specifications

Table B.1 shows three diagnostic tests for the baseline general specifications including redundant variable test, ommitted variable test, and residual normality test.

The first column gives the P values for a F test of the joint significance of the economic variables in the baseline general model. The null hypothesis is that ETA(-1), GRRTTL(-1), ROE(-1), and CTA(-1) are jointly insignificant. For the individual banks, the economic variables are only significant at the 5% level in Bank 10, the Industrial Bank Co., Ltd. and at the 10% level in 4 banks. For 10 of the 14 banks the economic variables are not significant. They are significant in pooled groups: JSCBs (joint-equity banks). They are also significant when the 14 banks are pooled using the fixed effect estimator, probably because the larger sample size has reduced the standard errors.

We have assumed one lag of the economic variables in the baseline general model. The second column gives the P values for a F test for adding a second lag. The null hypothesis is that ETA(-2), GRRTTL(-2), ROE(-2), and CTA(-2) are jointly significant. The second lag is

significant at the 5% level only in 2 banks: the bank 1 and 12, and at the 10% level in the bank 3. Among the groups it is significant at the 1% level in G-SIBs and 10% level in group SOCBs. Thus there is relatively little evidence to include a second lag of economic variables in the model. This is also evidence against second order serial correlation being important.

The third column gives P values for normality tests. Only 2 of the 14 banks fail the normality test but the heterogeneity among the banks means that all the groups and the pooled estimates fail the normality test. These tests suggest that our general specifications for the individual banks are reliable.

Table B.1 Baseline general specifications, diagnostic tests. Dependent variable: NLG.

Test	**Redundant variables test**	**Omitted variable test**	**Residual normality test**
F-statistic	**P-value**	**P-value**	**P-value**
Fixed Effects Panel			
14 banks	**0.000**	0.608	**0.000**
Individual banks (crossid)			
1	0.737	**0.012**	0.272
2	0.756	0.338	0.260
3	0.707	**0.079**	0.766
4	**0.071**	0.130	0.111
5	**0.065**	0.310	**0.000**
6	0.351	0.891	0.933
7	0.412	0.103	0.544
8	0.409	0.300	0.152
9	**0.070**	0.824	0.880
10	**0.001**	0.297	0.728
11	0.907	0.276	0.964
12	0.341	**0.022**	0.856
13	0.756	0.957	**0.000**
14	0.607	0.379	0.286
Groups of banks (Fixed Effects)			
SOCBs	0.168	**0.058**	**0.000**
JSCBs	**0.000**	0.472	**0.000**
CCBs	0.450	0.210	**0.000**
G-SIBs	0.115	0.003	**0.000**
G-SUIBs	0.001	0.508	**0.000**

Note: The bold green numbers denotes significance at the 10% level; the bold blue numbers at the 5% level; and the bold red numbers at the 1% level.

Chapter 4

Macroeconomic Interactions with Money in China

4.1 Introduction

The stability of money demand is a central issue in monetary economics (Dou, 2018; Lee et al., 2008). The success of monetary policy depends on whether there exists a steady-state relationship between money demand and its determinants. The central bank's effort to control money supply and select valid policy instruments crucially depends on the relationship between the quantity of money and some key indicators of real economy (Zuo and Park, 2011). All the money supplied by the central bank must be held by someone.

Given the importance of money demand and its stability, we focus on China's money demand after its reform and opening policy starting from 1978, a period dominated by China's transformation from a centrally planned to a market economy. In a centrally planned economy, money demand is not a meaningful concept, because the central bank controls the quantity of money held by households and firms (Delatte et al., 2014). Hence, the existence of stable money demand in China provides evidence for its transformation to a market economy. A understanding of the basic characteristics of money demand in China will also help the government to formulate money policy and make reasonable money adjustment. This chapter focuses on M2, the broad money aggregate.

In China money, renminbi, is issued by the People's Bank of China (PBoC) and banking institutions (including banks, rural credit cooperatives and finance companies). Money is held by non-bank and non-government sectors. M2 includes currency in circulation (banknotes and coins issued by the PBoC less the amount held by banking institutions); demand, time and savings deposits in national currency of resident nonbank, non-government sectors with banking institutions. In China, deposits account for a large portion of liabilities of banks,

which banks' lending relies on. Bank loan is a major part of domestic credit. Credit expansion in China is studied in Chapter 2 and historically has been accompanied by an expansion of broad money.

We investigate Chinese money demand from two angles. Firstly, we estimate a reduced-form vector auto-regression (VAR) model which incorporates a set of macroeconomic variables: real money, real income, real exports, inflation, and interest rates. To distinguish the impact of different reforms, we apply our model to quarterly data for three samples: the whole sample from 1980 to 2018, an early reform period from 1980 to 1992, and a late reform period from 1993 to 2018. Comparing the AICs and BICs of these three VAR estimates, there is evidence for a structural break in money demand in 1992. We therefore proceed with the analysis of estimates based on the two subperiods, particularly focusing on the Granger causalities between variables. Much research uses Choleski decomposition or alternative decompositions like Bakker and Gulde (2010) to estimate structural vector auto-regression (SVAR). But for the Choleski decomposition, impulse response functions (IRFs) are sensitive to variables ordering and omitting important variables may lead to major distortions in IRFs. Since there is no agreement on the restrictions needed to identify structural vector auto-regression, we estimate a reduced-form VAR and use generalized impulse response functions (GIRFs) to show the empirical patterns of response.

Secondly, Johansen cointegration is used to test the existence of long-run relationships among variables, particularly the existence of a long run money demand function and an IS curve determining income in the two sub periods. Our approach assumes that in long run equilibrium, money demand equals money supply, and we investigate whether we can recover the money demand function from the data, assuming that in the long run the PBoC supplys the money demanded at a particular level of income, interest rates, and other variables. We employ a vector error correction model (VECM) to capture the long run relationships and the short run adjustments between money, income and their determinants. We identify two long-run cointegrating vectors in both sub-periods, which can be interpreted as long-run IS and LM curves. This has not been found for China before. We find that exports are significant determinants of output in both sub-periods, consistent with China's pattern of export driven growth. The short-run adjustment equations towards these long-run equilibrium conditions can be interpreted as capturing money-supply adjustments, a Phillips curve and a Taylor rule.

Our contribution is threefold: Firstly, we use quarterly data from 1980 to 2018, which covers a longer timespan than most comparable studies. China has been undergoing a transformation from a centrally planned economy to a market-oriented market economy since 1978. Crucially, our sample includes the year, 1992, the starting point of Deng Xiaoping's reforms and therefore a pivotal part of China's economic transformation; Secondly, we try to

build an extended monetary demand decision model in an open economy which accords with China's economic transformation as well as its move to a more open economy, on the basis of an open economy IS-LM framework augmented by exports. So, in addition to money, income, interest rates and inflation rates, we also considers the impact of exports on the economy system; Third, we explicitly analyse the stability of Chinese money demand in a cointegration framework, investigating structural breaks, indicative of market reforms. Our VAR / VECM framework treats all variables endogeneous. We find two cointegrating vectors between the variables considered, driven by broad money and aggregate income, resembling an IS/LM type relationship between money demand and the real economy. We identify a long run money demand function and an export driven long run IS relationship over 1980-2018 from a conintegrating VAR in 5 variables allowing for regime shifts in 1992. These results are different from previous findings, which typically only reveal one long run relationship. These results provide important evidence on China's economic transition to a market-based system, based on stable money and goods market equilibria.

This paper is organized as follows. Section 4.2 is a literature review. Section 4.3 describes data and variables and does unit root tests. Section 4.4 outlines a system approach, where we introduce the theory of money demand; and set up a reduced-form VAR, and a dynamic VECM model. Section 4.5 shows the VAR analysis including specification and empirical results. Section 4.6 reports the cointegration analysis. Section 4.7 analyses the adjustment to long-run equilibrium of money and income. Section 4.8 concludes.

4.2 Literature review

There are a number of studies that evaluated the demand for money across a range of industrial and developing countries (see the survey of Sriram (2000)). It provids some reference points concerning the behavior of money demand in various countries. But China is different in many aspects such as it is transforming from a centrally planned economy to a market economy, which may makes its behavior of money demand different.

Over the past 30 years - starting with the paper by Chow (1987), there have been more than 60 papers on Chinese money demand. EI-Shagi and Zheng (2018) find that a substantial publication bias of these papers towards rejecting stability of money demand. By a meta study, which includes 61 studies on money demand in China, covering all those periods of the modern Chinese economic history, some using data going back to the 1950s, other having samples going to current times past the great recession, EI-Shagi and Zheng (2018) strongly suggest stable long run money demand in China. But it is not reasonable for using meta-analysis to mix the results of different Chinese sample periods. China's economic reforms

have undergone significant structural changes after 1978. Due to fundamental changes in institutions and a number of financial reforms, there are uncertainties in money demand and it is reasonable to examine the stability of money demand across different time periods. We review a selected number of studies on the Chinese money demand focusing on the period after 1978 in China, and particularly studies on structural breaks in the money demand function.

Most studies on Chinese money demand are based on the classical money demand theory and share a general specification. The general specification as stated in Sriram (2000) begins with functional relationship for the long-term demand for money: $\frac{M}{P} = f(S, OC)$ where the demand for real balances M/P is a function of the chosen scale variable (S) to represent the economic activity and the opportunity cost of holding money (OC). M stands for the selected monetary aggregate in nominal term and P for the price. But the findings of these studies are inconsistent, because they differ frequently in the specifications in terms of selection and representation of variables, modeling, estimation, and sample.

4.2.1 The measurement of money

Money refers to holdings of cash and deposits. There are several measures about monetary aggregates usually used in the money demand studies: M0 for currency comprised of notes and fractional currency in circulation in the market; M1 for narrow money composed of currency plus demand deposits of banks; and M2 for a broader monetary measure comprised of currency, demand deposits of banks, time deposits, savings, and client margin of security companies.

Chinese money demand has been estimated for various aggregates: M0 (Chen, 1997; Hafer and Kutan, 1994; Qin, 1994); M1 (Bahmani-Oskooee and Wang, 2007; Deng and Liu, 1999); and M2 (Baharumshah et al., 2009b; Hafer and Kutan, 1994; Huang and Huang, 2017). Chen (1989) indicates that currency in circulation is a preferable monetary measure to a broader money in determining the long-run effect of monetary policy actions in China. Hafer and Kutan (1994) find that currency accounts for a decreasing proportion from 60 percent by 1970 to about 35 percent by the late 1980s of M2, reflecting the advance of financial reforms in China and this raises the question of whether M0 or M2 yields the most reliable money demand relationship; and their evidence points to broader M2 measure as the preferred aggregate. Most recent studies use M2, which is also been focused by our study. In addition, our empirical models specify the money demand as a function of real balances consistent with theoretical models, which has been illustrated by Laider (1993).

4.2.2 Variables determining money and their measurement

The theory suggests that money demand depends on a transaction measure (scale variable) and an opportunity cost measure, but there are different ways of measuring these variables. The scale variable used in current studies differs: Chow (1987) uses national income, Yi (1993) uses real national income per capita; most studies use real GDP (Dou, 2018; He, 2017; Huang and Huang, 2017). The opportunity cost measure also differs: Baharumshah et al. (2009b) use seven-day inter-bank rate, Jiang (2016) uses nominal interest rate paid on 3-month time deposits by commercial banks, Huang (1994) uses real rate of interest rate on one-year term saving deposits, while Aliha et al. (2019) uses the lending rate.

With the opening of Chinese economy, some include exchange rate as an extra measure of opportunity cost in addition to interest rates, ie., reflecting the opportunity cost of holding domestic rather than foreign money (Dou, 2018; Mehrotra, 2008; Wu, 2009). To our knowledge, Mehrotra (2008) was the first to investigate the effects of the exchange rate on money demand, where a renminbi appreciation increases the demand for the Chinese currency, possibly through increased currency inflows that add to the domestic money supply. Wu (2009) finds that changes in the exchange rate do not affect money demand significantly, but expectations of a further renminbi appreciation since 2005 appears to induce more money demand. Dou (2018) finds that both expected exchange rate and capital mobility do not enter China's money demand function. He argues that the reason may be that the change in the renminbi exchange rate has been all time limited in a narrow band since 1994 and could not thereby offer any useful information in regression and capital items are at present still strictly controlled in China. As many of new financial instruments, transaction technologies and policy change such as regulation or deregulation have been gradually introduced and quickly developed in China since 1994, Dou (2018) also tries to introduce a dummy variable to capture the effects of financial innovation on the money demand function but fails.

We consider macro variables, which are expected to have an influence on Chinese money: real GDP to measure the scale of the economy and 1-year lending rate to measure the opportunity cost. From 1978, when China started the reform and opening policy, particularly from China joining World Trade Organization (WTO) in 2001, the exports have increasingly drive its economy. We include exports in the system, because they are a major determinant of GDP, which drives transactions demand for money.

4.2.3 Form of the equation

The early studies use standard estimation techniques tackled different monetary issues by estimating the demand for money in China. For example, Chow (1987) use a single static

equation estimation to capture the long-run money demand function and a standard lagged-adjustment specification to capture the short-run dynamics of money demand. Qin (1994) uses the general to simple dynamic specification modelling approach.

But Hafer and Kutan (1994) argue that a common feature of much recent work presumes that a long-run equilibrium relationship underlies the short-run dynamic models being estimated, but if such an equilibrium relationship does not exist, attempts to measure the short-run dynamics of a given specification are misdirected. So more recent studies such as Hafer and Kutan (1994) and Chen (1997) employ cointegration technique to establish the long run relationship between money and other variables. Based on integration and cointegration test findings, some researchers construct error correction (ECM) model to evaluate the dynamic adjustment process of money demand in China (Aliha et al., 2019; Deng and Liu, 1999; Huang, 1994). Dou (2018) uses a standard structural VAR model to analyze the determinants of money demand in China.

We employ a systematic approach, a reduced-form VAR and generalized impulse functions, which overcome the shortcoming of a structural VAR that the impulse response functions are sensitive to the ordering of variables; and a vector error correction model to capture the long run relationships and the short run adjustments between money, income and their determinants.

4.2.4 Money supply assumption

Most studies of Chinese money demand assume that the equation being estimated is a money demand function. But the treatment of money supply is often not discussed. Most researchers such as Bahmani-Oskooee and Wang (2007) and Baharumshah et al. (2009b) etc. regard the relationship between broad money M2 and other macrovariables as a money demand function, but (He, 2017) regard it as a money supply function.

We assume money demand equals money supply and the money market achieves an equilibrium. The PBoC controls over money supply and monitors changes in the money supply because of the belief that such changes affect the price levels, inflation, and output. In 1996, China determined the supply of M1 as the intermediate target of monetary policy and M0 and M2 as the observation target. The PBoC published the target values of M1 and M2 every year. Usually, there is a gap between the growth rate of the actual value and the target value (He, 2017). Since 2007, the PBoC has abolished the target growth rate of M1 and only that of M2 is published, which is also why we focus on M2. We assume that in the long run the PBoC supply the money demanded at a particular level of income, interest rates, and other variables. In the short run, we allow all the variables to be endogenous and the PBoC

can adjust interest rates (Taylor rule) or adjust money supply (McCallum rule) (Orphanides, 2007).

4.2.5 Time periods and treatment of structural changes

Starting from Chow (1987), there has been increasing attention on China's money demand for the time period from the 1950s to the early or mid or late 1980s or early 1990s such as Yi (1993), Hafer and Kutan (1994) and Chen (1997). There is also research on China's money demand for the time period from the 1980s to 2000s or recent years, such as Bahmani-Oskooee and Wang (2007) and Delatte et al. (2014). These studies is that they have dealt with definitions of money, the causal relationships between monetary aggregates and other macroeconomic variables, price, and interest rate Huang (1994).

Though these studies improve our understanding of China's monetary sector, they do not reflect the behavior during China's economic transition. Separate consideration of China's pre-reform period (before 1978) and the reform period deserves (post-1978) deserve further attention. China starts big reforms from Deng Xiaoping's southern tour in early 1992 and the 14th National People's Congress in October 1992, which was stated in government documents that they mark a new stage of China's socialist reform, opening up, and modernization drive. China starts financial reforms from 1978 and have further financial reforms in from around 1993, including a 16-point financial reform program in 1993. It may be reasonable to split the reform period into early stage (1978 to 1992) and later stage (1993-).

There are arguments about whether there is regime shift in the money demand during the reforming process. As pointed out by Prasad and Rajan (2006): the China's economic reform beginning in late 1970s took incremental and experimental processes, particularly, in the financial sector. The reform has been processed from local and small-scaled experiments to global and large-scaled experiments. If the result of the experiments turned out to be satisfactory, then they have been implemented elsewhere. Hence, Zuo and Park (2011) argue that the reform process is smooth and gradual without distinct or sharp regime shifts although the reforms themselves are very fundamental. Under the assumption of smooth reform, Zuo and Park (2011) employ a smooth time-varying cointegrating regression approach to take care of the parameter inconstancy proble in China money demand function. But a prevailing belief among Chinese economists is that China's economic reforms have undergone significant structural changes (Lee et al., 2008). Delatte et al. (2014) show some evidence by summarizing the economic theory, which predicts a number of developments for money demand during economic transition. Economic transition may imply monetisation, which implies an increasing volume of monetary transaction affecting all monetary aggregates, a

fact that may imply a drastic increase in money demand in the early stages of reform that then levels off progressively over time (Mukherjee, 1967).

Some papers study China's money demand in the process of economic transition and financial reform by splitting the whole sample into multiple sub-samples. For example, Qin (1994), Hafer and Kutan (1994) and Huang (1994) focus on the questions whether China's money demand relation has undergone significant structural changes from the pre-reform period to the early reform stage. But Hanson (2002) points out, a stability test based on a priori specified break date such as carried out in Hafer and Kutan (1994) is problematic. So, we specify a priori break date, 1992, on the basis of facts of reforms and patterns of variable, and then we test whether it is a break by econometric methods such as information criteria.

The main conclusion from these studies is that most studies suggest a long run money demand function exists in China whatever sample period they are using. Some studies use a time span covering both pre-reform and reform period, so their models do not reflect the behavior during China's economic transaction. Although some other studies assume that the reforms have an impact, they focus on a specific reform period, such as later reform period. Our study use quarterly data from 1980 to 2018, which covers a longer timespan than most comparable studies. A longer timespan including the year, 1992, the starting point of Deng Xiaoping's reforms and therefore a pivotal part of China's economic transformation, allows us to examine structural break in China's money demand function and to find the difference in the money demand between different reform periods under same framework.

4.2.6 Inconsistent results.

As stated in Judd and Scadding (1982), the studies about money demand share common important variables and in general, they bring forth relationship between the quantity of money demanded and a set of few economic variables linking money to the real sector of economy. So do the studies about the China's money demand. There are not only arguments about whether there exists a long run money demand function in China, but if there exists one, whether the determinants of money demand are consistent.

Zuo and Park (2011)'s survey of some studies on money demand in China shows that the income elasticity of money demand varies from 0.65 to 1.93 and the interest rate elasticity varies from -4.52 to 0.22. But Wu (2009) find that money demand does not appear very sensitive to interest rates, possibly reflecting their partial liberalization. Yi (2006) find that inflation has not any statistically positive impact on money demand in the long run, Mehrotra (2008) finds that inflation has a statistically positive impact, while Baharumshah et al. (2009a) finds a negative impact. The effect of other variables such as exchange rate differs too. There are also arguments about the influence of exchange rates on money demand. So the empirical

results of these studies are not robust about the effect of macroeconomic variables, even the so-called standard variables such as opportunity cost and inflation indicated by the money demand theory. This may be due to probable misspecifications, omission of important factors, and different sample used etc.

4.3 Data, variables and unit root tests

4.3.1 Data and variables

The sample is time series of quarterly data over 1980-2018 of money and macroeconomic variables at national level in the case of China. The data mainly comes from the CEIC (Global Economic Data, Indicators, Charts & Forecasts), DS (Datastream), Mohaddes and Raissi (2018), and NBSC (National Bureau of Statistics of China). We convert money (M), exports (X), 1-year lending rate (R) into real terms by CPI (Consumer Price Index) which is in 2010Q1 value. lm, ly, and lx stand for the natural logarithm of real money, real income, real exports, respectively. $D^y(lm)$, $D^y(ly)$, and $D^y(lx)$ stand for the annual growth of real money, real income and real exports, respectively in annual percent rates.[1] Table C.1 in Appendix C shows the variables and data information.

Table 4.1 gives descriptive statistics based on three periods: the whole sample period, 1981Q1-2018Q3; the early reform stage, 1981Q1-1992Q4; and the later reform stage, 1993Q1-2018Q3.[2] For the growth variables ($D^y(lm)$, $D^y(ly)$, and $D^y(lx)$), inflation (PI), and nominal interest rate (R), their mean, median, or standard deviation in the early reform stage are bigger than their corresponding ones in the later reform stage.[3] This might imply a structural break in 1992. The first subgraph of Figure 4.1 illustrates that exports growth is more volatile with a larger fluctuation range than money followed by income; and the growth of money, income and exports are relatively stable in the later reform stage with the exception of post-crisis (around 2008-2011). The second subgraph of Figure 4.1 shows that money as share of income increases rapidly and overpassed 100% in 1993. The exports share in average is 11% in the early reform stage and has been 24% in the later reform stage, although it has a decreasing trend after financial crisis. The later reform period is a new stage of China's socialist reform, opening up, and modernization drive, when the socialist market

[1] $D^y(lm) = \frac{lm_t - lm_{t-4}}{lm_{t-4}} * 100$; $D^y(ly) = \frac{ly_t - ly_{t-4}}{ly_{t-4}} * 100$; $D^y(lx) = \frac{lx_t - lx_{t-4}}{lx_{t-4}} * 100$.

[2] Table 4.1 shows descriptive statistics starting from 1981Q1 rather 1980Q1, because growth variables are calculated by taking the difference of the natural logarithm of variables.

[3] The only exception is that the nominal interest rate in the later reform period has a bigger standard deviation.

economic system is gradually improved. These reforms and improvements provide reliable guarantee for stable economic growth.

Comparing the difference between variables, the average money growth is larger than of exports followed by of income; and the standard deviation of money is smaller than of exports and larger than of income in both periods. The average money growth is 16.67% in the early reform stage and 13.13% in the later reform stage. The average income growth is 9.24% in the early reform stage, and 9.07% in the later reform stage. The rapid income growth in the later reform period mainly happened after China becoming a member of the WTO in December 2001 and before the global financial crisis. Exports, as a composition of income, drived the income growth during this period (see the second subgraph of Figure 4.1). Income still keeps a rapid growth (above 9%) between 2009Q3 and 2011Q4, which may be influenced by the 4-trillion-yuan stimulus package adopted by the Chinese government.[4] The income growth shows a sharp decreasing trend from 2010Q1 (11.51%) to 2018Q3 (5.94%).

Table 4.2 gives the contemporaneous correlation matrix between variables. In the early reform stage, money growth has significant correlations with every other variable, particularly strong correlations with exports growth, inflation and real interest rates; and income growth has significant correlations with money growth, 0.3, and with nominal interest rates, -0.27; and exports has significant correlations with money growth, 0.71, inflation, -0.59, nominal interest rates, -0.42, and real interest rates, -0.54. In the later reform stage, all the correlations are significant except the correlation between money and nominal interest rates. The correlations of money with every other variable in the later reform period are weak with absolute numbers smaller than 0.32, so does of exports (except with income) with absolute numbers smaller than 0.33. The correlation coefficients of income with every other variable except money in the later reform period are bigger than the early reform stage. Different from the early reform stage, the correlation of money with exports and nominal interest rates, of income with inflation and both nominal and real interest rates, and of exports with every other variable excluding income are opposite in the later reform period. Inflation has a strong and statistically significant positive correlation with nominal interest rates, particularly in the later reform period with a number of 0.77, which may reflect that the interest rates is a monetary policy tool to manage inflation.

[4] In September 2008, after the outbreak of the global financial crisis, China's economic growth slowed down rapidly, with negative exports growth and a large number of migrant workers returning home. The economy was at risk of a hard landing. In response to this crisis, the State Council approved a plan to invest 4 trillion yuan in infrastructure and social welfare by the end of 2010. The Chinese government launched ten measures, for example, providing funds for infrastructure projects and housing developments, in November 2008 to further expand domestic demand and promote steady and rapid economic growth. According to preliminary calculations, the implementation of these ten measures would require an investment of about 4 trillion yuan by the end of 2010.

Table 4.1 Descriptive statistics of variables.

1981Q1-2018Q3:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
Mean	14.26	9.13	12.43	4.92	7.11	2.34
Median	13.86	8.89	12.24	2.44	6.56	3.00
Max.	33.58	14.24	55.87	27.97	12.06	8.63
Min.	-8.51	3.83	-33.34	-1.97	4.35	-14.45
Std. Dev.	6.87	2.56	15.54	6.30	2.07	4.44
Obs.	151	151	151	151	151	151
1981Q1-1992Q4:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
Mean	16.67	9.24	15.33	6.69	8.10	1.62
Median	18.57	9.57	17.03	4.81	7.92	2.89
Max.	33.58	14.15	40.44	27.97	11.34	7.73
Min.	-8.51	3.83	-33.34	1.50	5.04	-14.45
Std. Dev.	9.13	3.36	16.90	6.54	1.51	5.06
Obs.	48	48	48	48	48	48
1993Q1-2018Q3:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
Mean	13.13	9.07	11.07	4.09	6.65	2.68
Median	12.74	8.71	8.58	2.13	5.85	3.19
Max.	31.65	14.24	55.87	26.70	12.06	8.63
Min.	3.05	5.94	-27.94	-1.97	4.35	-12.41
Std. Dev.	5.21	2.11	14.76	6.03	2.13	4.10
Obs.	103	103	103	103	103	103

Note: The unit for each variable is percent annual rates (% pa).

In summary, real broad money in China has grown rapidly and the money share in GDP has increased to above 200% since 2016. The money share has a trough in 2008, but it increases dramatically after. Real money growth is volatile with a wide range, while real income growth is within a tight range. The contribution of exports to income shows an increasing trend before crisis and a decreasing trend after. Inflation varies a lot and it was high in 1980s and early 1990s but has been low since then. From 1996 when China's interest rate liberalization started to 2003, both the benchmark deposit and lending interest rates have been falling for eight consecutive years and kept at a low level after. China controls interest rates by setting restrictions on it and interest rate policy has become an important tool to regulate inflation and economic growth. Since 2013, China has decided to fully liberalize the control of interest rates on loans from financial institutions. The contemporaneous relationships between variables are weak in the later reform stage. The descriptive statistics and graph patterns of variables and the different even opposite correlations between variables

Table 4.2 Correlation matrix.

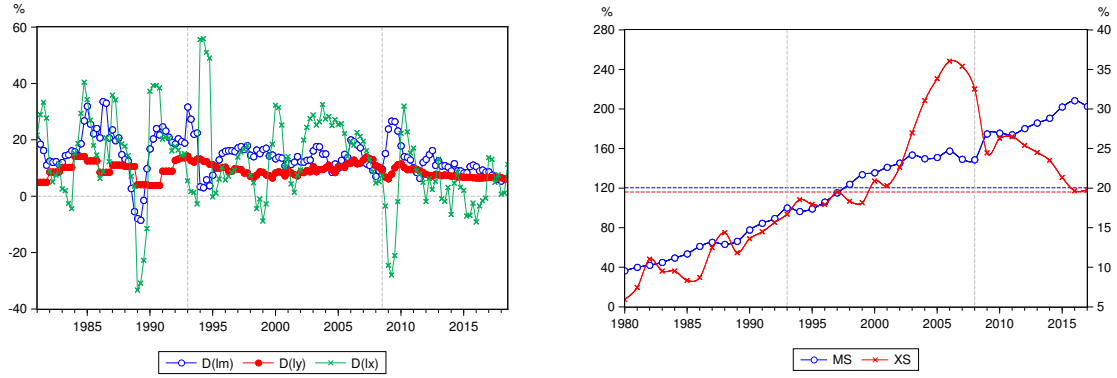
1981Q1-2018Q3:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
$D^y(lm)$	1	0.29***	0.21***	-0.38***	0.03	0.48***
$D^y(ly)$	0.29***	1	0.31***	0.22***	0.21***	-0.20**
$D^y(lx)$	0.21***	0.31***	1	0.02	0.06	0.00
PI	-0.38***	0.22***	0.02	1	0.70***	-0.95***
R	0.03	0.21***	0.06	0.70***	1	-0.46***
r	0.48***	-0.20**	0.00	-0.95***	-0.46***	1
1981Q1-1992Q4:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
$D^y(lm)$	1	0.30**	0.71***	-0.76***	-0.36**	0.74***
$D^y(ly)$	0.30**	1	0.17	-0.19	-0.27***	0.14
$D^y(lx)$	0.71***	0.17	1	-0.59***	-0.42***	0.54***
PI	-0.76***	-0.19	-0.59***	1	0.50***	-0.97***
R	-0.36**	-0.27***	-0.42***	0.50***	1	-0.28*
r	0.74***	0.14	0.54***	-0.97***	-0.28*	1
1993Q1-2018Q3:						
	$D^y(lm)$	$D^y(ly)$	$D^y(lx)$	PI	R	r
$D^y(lm)$	1	0.27***	-0.29***	-0.20**	0.12	0.32***
$D^y(ly)$	0.27***	1	0.44***	0.56***	0.49***	-0.51***
$D^y(lx)$	-0.29***	0.44***	1	0.33***	0.18*	-0.33***
PI	-0.20**	0.56***	0.33***	1	0.77***	-0.95***
R	0.12	0.49***	0.18*	0.77***	1	-0.54***
r	0.32***	-0.51***	-0.33***	-0.95***	-0.54***	1

Note: Null hypothesis: the correlation coefficient between variables is zero. * denotes to reject the null hypothesis at 10% significance level, ** at 5% significance level and *** at 1% significance level.

in the early and later reform stages may imply a structural break, a regime shift, in the progress of transforming to a market economy.

In the Chapter 1, we have discussed how the monetary authority targets the benchmark interest rates to regulate the deposits and lending in the economy. We find that the deposit and lending interest rates roughly go up and down together, so we can use either deposit rate or lending rate in the empirical model analysis of this chapter. We choose lending rate, though the results are similar with deposit rates, results for the deposit rate are given in the Appendix C.

Fig. 4.1 Real money growth, real income growth and real exports growth; money and exports as share of GDP.



Note: In the left-hand subgraph, the blue line represents real money growth ($D^y(lm)$), the red line represents real income growth ($D^y(ly)$), and green line represent real exports growth ($D^y(lx)$). In the right-hand subgraph, the blue line represents money share in the GDP (MS), and the red line represents exports share in the GDP (XS); the blue dashed line represents the average money share in the GDP, and the red dashed line represents the average exports share in the GDP.

4.3.2 Unit root tests

For completeness and cointegration analysis in the later sections, we conduct augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to check whether each time series variables is stationary. However, unit root tests are sensitive to the form of the test, treatment of deterministic terms, interpret and trend, treatment of serial correlation, seasonality, structural breaks, etc. So, the tests can only be indicative, not conclusive.

For the whole period, at 5% significance level, both the ADF and the PP test results show that the null hypothesis of a unit root (non-stationary) in the levels of lm, lx, PI, and R could not be rejected. However, when the tests are performed on the first differences of the same variables, the null hypothesis of a unit root is rejected by both tests for lm, lx, PI, and R at 5% significance level, suggesting that these four variables can be integrated of order 1 (i.e. I(1)). The ADF test suggests ly is I(1) at 10% significance level, while the PP test suggests ly is integrated of order 0 (i.e. I(0)). The test results for the later reform period are similar with the whole period. For the early reform period, the ADF test suggests lm, lx, PI (at 10% significance level) are I(0), ly is I(2), and R is I(1); the PP test results are different which suggests that lm, PI and R (at 10% significance level) are I(1), and ly and lx are I(0). We will treat them all as I (1).

4.4 Model

4.4.1 Money demand theory

Below we estimate a system of equations for the five variables of interest, each of which we treat as endogenous. The underlying theory is of a classical IS-LM model in the long run, with short run adjustment to a long run money demand function and ouput equation. As noted above we assume money demand equals money supply in long run equilibrium. We assume that in the long run the PBoC supply the money demanded at a particular level of income, interest rates, and other variables. In the short run, we allow all the variables to be endogenous and the PBoC can adjust interest rates (Taylor rule) or adjust money supply (McCallum rule). The adjustment process may also reflect a short run Phillips curve determining inflation.

The most basic classical transaction motive can be illustrated with reference to the Quantity Theory of Money. According to the equation of exchange $MV = Py$, where M is the stock of money, V is its velocity (how many times a unit of money turns over during a period of time), P is the price level and y is real income. Consequently, $Y = Py$ is nominal income or in other words the number of transactions carried out in an economy during a period of time. Rearranging the above identity and giving it a behavioral interpretation as a demand for real money we have $\frac{M}{P} = \frac{y}{V}$, where M is nominal money demand. Hence demand for money is a function of price and income, as long as its velocity is constant. But often it is assumed that the velocity is not constant but a function of the rate of interest that is $V = V(R)$, where R is nominal interest rates. If interest rates are high, people will try to make the money go faster, which can be explained by the Baumol-Tobin inventory model. So the amount of money demanded for transactions is also a function of nominal interest rates. Therefore, a generalized money demand function, in which we relax the assumption that the coefficient of income is one, can be written as:

$$\frac{M}{P} = K(1+R)^{\alpha} y^{\beta}, \tag{4.4.1}$$

where K is a constant and $V(R) = (1+R)^{-\alpha}$. It is assumed that in the long-run the monetary authority supplies the money demanded and influences money demand through interest rates.

Furthermore, taking the logarithm of both sides of the generalized money demand function (4.4.1) gives:

$$lm \approx lK + \alpha R + \beta ly, \tag{4.4.2}$$

where lm, ly, and lK are natural logarithm of real money demand, real income, and constant K. The real money demand is a function of real income and nominal interest rates. We allow for either the nominal or real interest rates to matter by including inflation. This gives us an extended long-run real money demand function that determines equilibrium real money balances, lm_t^*:

$$lm_t^* = \beta_0 + \beta_1 ly_t + \beta_2 PI_t + \beta_3 R_t, \tag{4.4.3}$$

where PI_t is inflation.

If the long-run demand for money is stable, then a monetary policy which consists of a monetary rule which targets the growth rate of some monetary aggregate (such as M2) can help to stabilize the economy or at least remove monetary policy as a source of macroeconomic volatility. Additionally, if the demand for money does not change unpredictably then money supply targeting is a reliable way of attaining a constant inflation rate. This can be most easily seen with the theory of money equation given above.

4.4.2 VAR

The above theory supplies an useful framework to study money and income, but it is static. We need dynamic adjustment to allow for interactions between variables. We are looking at the relationship between money, income, exports, inflation, and interest rates. A single equation approach, such as equation (4.4.3), treats all independent variables as exogeneous, but we will treat all of them endogeneous as all jointly determined. In addition, since China has been an exports driven economy, we add exports as determinants of income.

Since all these variables are endogenous, following Sims (1980), we use a vector autoregression (VAR), a dynamic multivariate model, allowing all variables to enter in the same way. The objective of the VAR is to capture the linear interdependencies among multiple time series, and to examine the dynamic response of the system to shocks. VAR modelling does not require as much knowledge about the forces influencing a variable and the only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally.

A structural m-variable vector autoregression (SVAR) with p lags takes the form:

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \cdots + \Gamma_p x_{t-p} + \varepsilon_t, \tag{4.4.4}$$

where x_t is a (m×1) vector of variables; ε_t is a (m×1) vector of structural innovations; B is the (m×m) matrix of coefficients in the current period; Γ_0 is a (m×1) vector of constants; Γ_1 is the (m×m) coefficient matrix of variables with one lag; Γ_p is the (m×m) coefficient matrix of variables with p lags. It is assumed that (i) it does not matter for whether variables

in the x_t are stationary or not; (ii) the variance/covariance matrix of $\varepsilon_{it}, i = 1,2,...m.$ and $\varepsilon_{jt}, j = 1,2,...m.$ is Ω; (iii) ε_t is a white-noise process. The structural m-variable VAR with p lags contain m^2 parameters in B, (m×1) parameters in Γ_0, (p×m^2) in Γ_1 to Γ_p, and $(m^2+1)/2$ parameters in Ω.

The SVAR model (4.4.4) cannot be estimated by OLS since the contemporaneous effect between variables, which leads to the correlation between a dependent variable in one equation with error terms in other equations. For example, x_{2t} is correlated with ε_{1t}, because ε_{1t} has a contemporaneous effect on x_{1t} and x_{1t} has a contemporaneous effect on x_{2t}. Therefore, we need to transform the system of model (4.4.4) into a reduced-form VAR which can be estimated. Premultiplication by B^{-1}, we obtain a p order and m-variable reduced-form VAR as follows:

$$x_t = A_0 + A_1 x_{t-1} + \cdots + A_p x_{t-1} + e_t, \tag{4.4.5}$$

where $A_0 = B^{-1}\Gamma_0$, $A_1 = B^{-1}\Gamma_1$, $A_p = B^{-1}\Gamma_p$, and $e_t = B^{-1}\varepsilon_t$. e_t is a vector of error terms. It is assumed that (i) the variance/covariance matrix of $e_{it}, i = 1,2,...m.$ and $e_{jt}, j = 1,2,...m.$ is Σ; (ii) e_t is a white-noise process. The m-variable reduced-form VAR with p lags contain (m×1) parameters in A_0, (p×m^2) in A_1 to A_p, and $(m^2+1)/2$ parameters in Σ.

The reduced-form VAR (4.4.5) does not have the problem of feedback inherent in a SVAR process, so it can be estimated by OLS. We then can get estimated values of parameters in the reduced-form system. However, we still cannot recover the parameters in model (4.4.4) by the estimates in the reduced-form VAR, because the number of parameters of the estimated reduced-form VAR model is fewer than the number of parameters of the SVAR. Only if we impose m^2 extra identification restrictions between parameters in the SVAR, can we calculate parameters in the SVAR system. These restrictions are not testable and economists tend not to agree on what constitute plausible restrictions.

Instead of using orthogonalised impulse response functions from the Choleski decomposition we use generalized response functions (GIRFs) from the VAR with lag 1:

$$x_t = A_0 + A_1 x_{t-1} + e_t, \tag{4.4.6}$$

$$e_t = B^{-1}\varepsilon_t,$$

$$Ee_t e_t^{'} = \Sigma = B^{-1}\Omega B^{-1'}.$$

We can just calculate GIRFs using estimated parameters in A_1 and Σ. The impulse response function is then given by the moving average representation of (4.4.6), which can be writen

in terms of the e_t sequence:

$$x_t = c + \sum_{i=0}^{\infty} \Theta_i e_{t-i}, \tag{4.4.7}$$

where the e_t are not diagonal and Θ_i $(= A_1^i)$ are the functions of parameters from the reduced-form VAR model with lag 1. We can always use estimated $\hat{A_1}$ and $\hat{\Sigma}$ from the reduced-form VAR rather than the structural estimates $\hat{B}$ and $\hat{B_1}$ to calculate the GIRFs.

The generalized impulse response functions of reduced-form VAR show the empirical pattern of responses without having to make any identifying assumptions on B and Ω. Without any restrictions, we cannot identify some within period effects and distinct uncorrelated shocks, but we do not need to. Therefore, this paper will proceed based on the reduced-form VAR without any restrictions.

4.4.3 VECM

The VAR is difficult to interpret, but we can restrict it to get a vector error correction model (VECM) which may allow us to identify the long-run cointegrating relationships to which we can give an economic interpretation. Calza et al. (2003) stated that, "The use of a VECM allows to specify both the long-run and the short-run dynamics of the model, while also capturing potential endogeneity of the determinants of credit demand. In particular, while the cointegrating vector is generally interpreted as a long-run equilibrium relationship, the estimates of the short-term dynamics help to characterise the process of adjustment towards the equilibrium".

We set a m-variable quarterly vector error correction model as follows,

$$\Delta x_t = C + \Pi x_{t-1} + \sum_{i=1}^{p} \Psi_i \Delta x_{t-i} + v_t, \tag{4.4.8}$$

where x_t is a (m×1) vector of variables which includes *lm*, *ly*, *lx*, *PI* and *R*; C is a vector of intercepts; Π is the (m×m) matrix of coefficients for x_{t-1}; Ψ_i is the (m×m) matrix of coefficients for Δx_{t-i} and it captures the short-run relations between variables; v_t is a vector of error terms; p is lag length. It is assumed that v_t is a white-noise process.

If there is cointegration, assume that there are r cointegrating relations $Z_t = \beta x_t$, which are I(0), where β is r×m coefficient matrix and it captures the long-run relations between variables, then

$$\Delta x_t = C + \alpha Z_{t-1} + \sum_{i=1}^{p} \Psi_i \Delta x_{t-i} + v_t, \tag{4.4.9}$$

where α is m×r matrix, and $\Pi = \alpha\beta$. αZ_{t-1} is the error correction term (ECM) or disequilibrium term. α are adjustment coefficients that show the proportion of the disequilibrium removed in any period. α and β are the parameters we focus on.

In the VECM, now we have split $\Pi = \alpha\beta$ into adjustment coefficient α and cointegrating vector β. There is no unique way to do this since $\Pi = \alpha\beta = (\alpha P)(P^{-1}\beta) = \alpha^*\beta^*$ are observationally equivalent with identical log-likelihoods, AICs and BICs. We have to choose a P matrix, which is $r \times r$, where r is the number of cointegrating vectors. To identify α and β, we need to impose r relations on each cointegrating vector β. So if $r = 2$, we need 4 restrictions and 2 on each cointegrating equation. One restriction on each equation will be a normalization restriction, the coefficient equals -1, this determines which is regarded as the dependent variable explained by the equation. To choose appropriate dependent variable, we also need to consider two criteria: the relevance for a particular purpose and consistency with other information such as economic theory. For example, one purpose of this study is to find the interactions of money with other macrovariables, so we will impose a normalization restriction on the coefficient of money and make it as a dependent variable. Then we hope to get a long-run money cointegrating equation which is consistent with money demand theory.

4.5 VAR analysis

We proceed based on a reduced-form VAR model. The VAR involves choices about what set of variables to model, and what length to use etc. We mainly consider three criteria to choose appropriate variables and lag length. The first one is the relevance for a particular purpose, e.g., forecasting which needs very simple models, policy analysis which needs control variables, and testing hypotheses. Different purposes require different models. Our purpose is to explain what determines money demand and how money affects other macro variables. GIRFs help to achieve our purpose. The second criterion is the consistency with other information, e.g., economic theory and institutional factors. The third criterion is the statistical adequacy which depends on fit (e.g., maximized log likelihood) and number of parameters. AIC and BIC weight the maximized log likelihood and number of parameters differently and BIC puts a large number of penalties on the number of parameters.

4.5.1 Specification

We select variables for the reduced-form VAR model by the motivation of interactions between real money (lm_t), real income (ly_t) and several other macroeconomic variables: real exports (lx_t), inflation (PI_t), and nominal lending interest rate (R_t), and we also try to

examine their dynamic relationships that is our research purpose. Exports measure the effect of foreign factors on internal market. Nominal lending interest rate, R_t, is a measure of opportunity cost and monetary policy stance. These variables are expected to affect each other. The selection of the number of variables trades off between using a parsimonious model to avoid overfitting, while guarding against omitted variable bias that can undermine the interpretation of the VAR results (Bruno and Shin, 2015). In addition, the selection of number of variables are restricted by sample observations. So, our VAR consists of five variables: lm_t, ly_t, lx_t, PI_t, and R_t. The data is from 1980Q1 to 2018Q3. We estimate VARs based on three periods: the whole reform period, 1980Q1-2018Q3; the early reform stage, 1980Q1-1992Q4; and the later reform stage, 1993Q1-2018Q3.

Information criteria give conflicting indications as to the correct number of lags. So we examine the statistical adequacy of VARs for different lag order. A good VAR should not have residual serial correlation problem and heteroskedasticity problem. The VAR residuals should be normally distributed.[5] Furthermore, a good VAR model needs to be stable, which means that all inverse roots of its characteristic polynomial must lie inside the unit circle. In our case, the GIRFs results do not make much difference across models with different lags. The difficulty is that the above criteria suggest inconsistent choice of lag order.

After considerable experimentations, we proceed with a 5-variable reduced-form VAR with 5 lags for each period. The five variables include real money (lm_t), real income (ly_t), real exports (lx_t), inflation (PI_t), and nominal lending interest rate (R_t). Different from the whole and the later reform periods, the VAR includes a trend for the early reform period. Table 4.3 shows the AIC and BIC of VARs. Obviously, the sum of AICs for VAR based on early reform period and for VAR based on the later reform period is much bigger than the AIC for VAR based on the whole period, whether the VAR includes a trend. So does BIC. This suggests a structural break in 1992. So it is better to proceed with VARs on the subsamples rather the whole period. The VAR for the early reform period does not have residual serial correlation problem and has normal residual distribution; and the VAR for the later reform period has residual serial correlation and heteroskedasticity problems and has not normal residual distribution. We could try to deal with these problems using longer lags and dummy variables for outliers, but it seems better to maintain the VAR for comparability with the early period. Having two different specifications would make comparison difficult. In the following sections, we mainly present the model results for subsamples by evidence from estimates, Granger causality tests, generalized impulse response graphs.

[5] Juselius (2006) argued that it is not necessary for the residuals in the VARs to have normal distribution, if this is caused by excess kurtosis.

Table 4.3 VAR models, information criterion statistics.

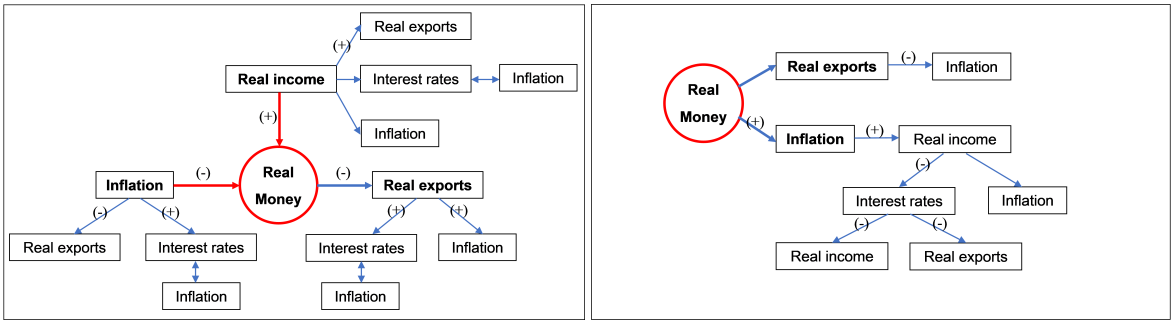
VAR: 1980Q1-2018Q3				VAR: 1980Q1-1992Q4				VAR: 1993Q1-2018Q3			
Trend	**Constant**	**AIC**	**BIC**	**Trend**	**Constant**	**AIC**	**BIC**	**Trend**	**Constant**	**AIC**	**BIC**
Yes	Yes	**-8.36**	-5.65	Yes	Yes	**-8.10**	**-2.79**	Yes	Yes	-10.52	-7.06
No	Yes	-8.34	**-5.73**	No	Yes	-7.64	-2.52	No	Yes	**-10.55**	**-7.22**

4.5.2 VAR estimates

We mainly focus on the significant interactions of money and income with other variables in the VAR system. Figure 4.2a shows the linkages between money and the other variables for the early reform stage, 1980Q1-1992Q4. This suggests that the past values of income positively and inflation negatively affect money; and past values of money negatively affect exports. No any other variable in the system directly affect income in the early reform stage, but past values of income directly affect every other variable in the system including money, exports, interest rates, and inflation. Figure 4.2b shows the VAR estimates for the later reform stage, 1993Q1-2018Q3, suggesting that no any other variable directly affect money in the later reform stage; past values of money significantly affect exports, and marginally significantly affect inflation. Inflation has a significant positive effect on income in the later reform stage, and the past values of income directly affect inflation and interest rates but not money and exports.

It is difficult to interpret the estimates of VAR model, particularly when there are many lags. These estimates show there exist direct or indirect interactions between variables in the system. But it is obvious there are difference about these interactions between the early reform stage and later reform stage.

Fig. 4.2 VAR estimates.



(a) VAR estimates for 1980Q1-1992Q4. **(b)** VAR estimates for 1993Q1-2018Q3.

4.5.3 Granger causality tests

Table 4.4 shows the results of Granger causality tests using the Wald Chi-squared statistics. The significance of the Granger causality is determined using asymptotic critical values. The test indicates that money is predicted by inflation in the early reform period, and by interest rates in later reform period; income is predicted by inflation in the early reform period, and by exports, inflation and nominal interest rates in the later reform period. Both money and income play a role in predicting exports and inflation in both reform periods; and income also plays a role in predicting nominal interest rate in the later reform period. Every variable is jointly influenced by the other variables in the system with statistical significance in each reform stage excluding income in the early reform stage.

Table 4.4 Granger causality test: P-value of Chi-sq statistics.

1980Q1-1992Q4:

		Causal variable				
		lm	*ly*	*lx*	*PI*	*R*
Causalled variable	*lm*	-	0.437	0.267	0.025(**)	0.728
	ly	0.397	-	0.579	0.023(**)	0.599
	lx	0.019(**)	0.001(***)	-	0.000(***)	0.182
	PI	0.021(**)	0.000(***)	0.012(**)	-	0.011(**)
	R	0.617	0.168	0.068(*)	0.031(**)	-

1993Q1-2018Q3:

		Causal variable				
		lm	*ly*	*lx*	*PI*	*R*
Causalled variable	*lm*	-	0.100	0.988	0.122	0.063(*)
	ly	0.116	-	0.095(*)	0.015(**)	0.050(**)
	lx	0.000(***)	0.000(***)	-	0.428	0.264
	PI	0.001(***)	0.002(***)	0.004(***)	-	0.803
	R	0.110	0.059(*)	0.375	0.014(**)	-

Note: Null hypothesis: x_i does not Granger cause $x_j, i \neq j$. * denotes to reject the null hypothesis at 10% significance level. ** denotes to reject the null hypothesis at 5% significance level. *** denotes to reject the null hypothesis at 1% significance level.

Table 4.5 5-variable VAR: residual correlation matrix.

1980Q1-1992Q4:

	lm	*ly*	*lx*	*PI*	*R*
lm	1	-0.001	0.419***	-0.527***	-0.355
ly	-0.001	1	0.155	0.215	0.149
lx	0.419***	0.155	1	0.321	-0.401***
PI	-0.527***	0.215	0.321	1	0.136
R	-0.355	0.149	-0.401***	0.136	1

1993Q1-2018Q3:

	lm	*ly*	*lx*	*PI*	*R*
lm	1	0.039	-0.240**	-0.162	-0.167**
ly	0.039	1	0.234**	0.308***	0.122
lx	-0.240**	0.234**	1	0.005	-0.065
PI	-0.162	0.308***	0.005	1	-0.028
R	-0.167**	0.122	-0.065	-0.028	1

Note: Null hypothesis: the correlation coefficients between variables are zero. * denotes to reject the null hypothesis at 10% significance level. ** denotes to reject the null hypothesis at 5% significance level. *** denotes to reject the null hypothesis at 1% significance level.

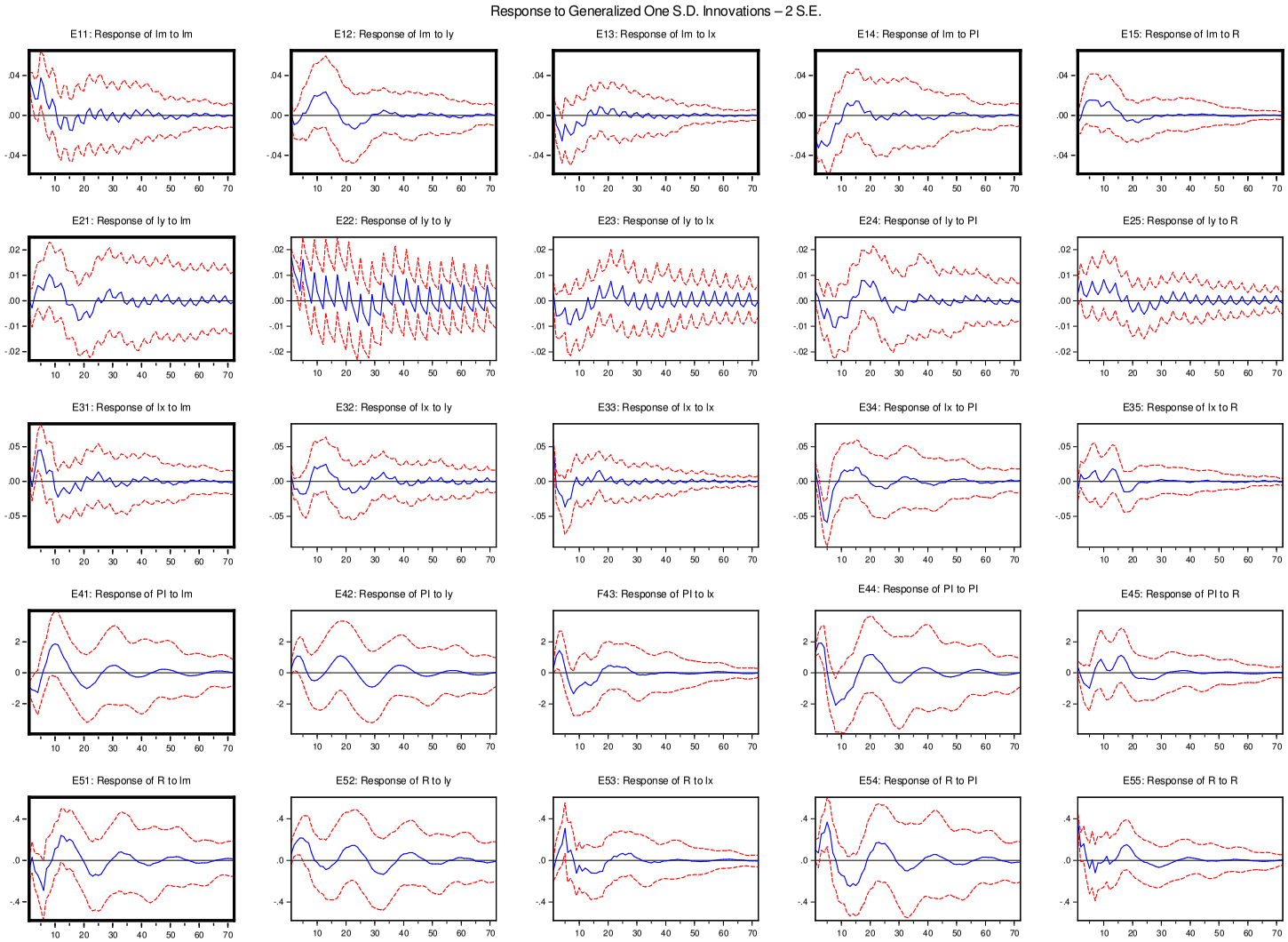
4.5.4 Generalized impulse response functions

Before proceeding to the GIRFs, Table 4.5 reports the residual correlation matrix of VARs. In the early reform stage, the within period residual correlation of money with exports is 0.42 and with inflation is -0.53; in the later reform stage, the correlation of money with exports is negative, -0.24, and with nominal interest rates is -0.17. For the income, it does not show any significant correlations with other variables in the early reform period, but shows significant and positive correlations with exports and inflation in the later reform period. Exports matter for money in both sub reform periods although with opposite coefficient signs. Money and income do not show significant correlations in either period.

Figure 4.3 graphs the GIRFs for the early reform period. The standard errors of each equation in the VAR system with *lm*, *ly*, *lx*, *PI*, and *R* as dependent variables are 3.55%, 1.68%, 4.99%, 1.36%, 0.37%, respectively. Subgraphs, E12, E13, E14, and E15 show the impacts of a shock to other variables on money in the early reform period. A one standard deviation positive shock to inflation represents a 1.36% increase in inflation, which decreases money in quarters 1-5 with a maximum of 3.26% (E14). The response of money to a shock of income, exports and interest rates does not show any statistical significance. Subgraphs, E11, E21, E31, E41, and E51 show the impacts of a money shock on variables in the system in the early reform period. A one standard deviation positive shock to money represents a 3.55% increase in the natural log of real money. A positive money shock predicts future increases in money itself in quarters 1-2, and 5 (E11), in exports with a maximum of 3.67% in quarters 4-5 (E31), and future decreases in inflation with a maximum of 1.9% in quarters 1-2 (E41). Income shows jagged fluctuations across zero to other shocks but only with significance to a shock to nominal interest rates, which indicates the seasonality of variables. A positive income shock shows significant positive impact on inflation (E42) and nominal interest rates (E52) with significance in some of the early quarters.

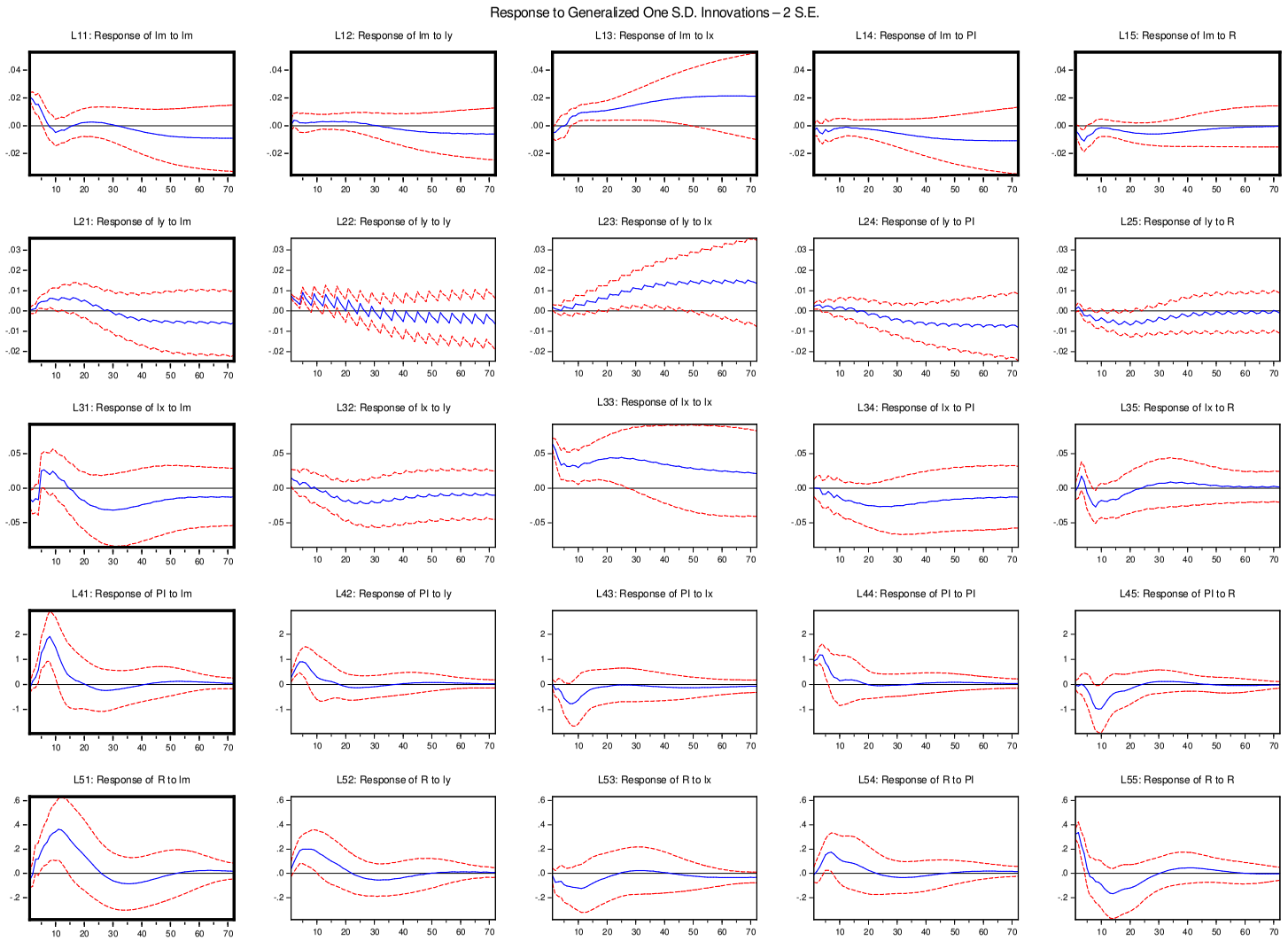
Figure 4.4 graphs the GIRFs for the later reform period. The standard errors of each equation in the VAR system with *lm*, *ly*, *lx*, *PI*, and *R* as dependent variables are 2.09%, 0.73%, 6.38%, 0.94%, 0.32%, respectively. Subgraphs, L12, L13, L14, and L15 show the impacts of a shock to other variables on money in the later reform period. A one standard deviation shock to exports represents a 6.38% increase in exports, which increases money in quarters 8-49 with numbers between 0.7% and 2.1% (L13). A positive shock to nominal interest rates has negative impacts on money with significance in quarters 3-4 (L15). The response of money to a shock of income and inflation does not show any statistical significance. Different from the early reform period, Subgraphs, L11, L21, L31, L41, and L51 show a money shock has significant positive impacts on every variable including future money itself in the later reform period. A one standard deviation shock to money represents

Fig. 4.3 GIRFs of 5-variable VAR for the early reform period.



Note: The blue solid lines show the generalized impulse response functions and the red dashed lines represent 95% confidence bands. The response standard errors are analytic.

Fig. 4.4 GIRFs of 5-variable VAR for the later reform period.



Note: The blue solid lines show the generalized impulse response functions and the red dashed lines represent 95% confidence bands. The response standard errors are analytic.

a 2.09% increase in the natural log of real money. A positive money shock predicts future increases in money itself in quarters 1-5 (L11). A positive one standard deviation shock to money significantly increases income by 0.37%-0.65% in quarters 4-10 and 12 (L21), exports by 2.53% in quarter 5 (L31), inflation by 0.58%-1.92% in quarters 4-10 (L41), and interest rates by 0.18%- 0.36% in quarters 5-14 (L51). Income increases facing a positive shock to money, exports, and inflation with significance in some of the early quarters. But income does not show significant response to a shock to the nominal interest rates (L25), which is different from the early reform period. A positive income shock shows significant positive impact on exports (L32), inflation (L42) and nominal interest rates (L52) with significance in some of the early quarters.

In summary, each variable reacts significantly to its own shocks. The GIRFs for the early reform period reveals correlations of money with exports and inflation, but not with income and nominal interest rates. Only an inflation shock has a significant effect (positive) on money in the early reform period. The GIRFs for the later reform period reveals correlations of money with every other variable, but only an exports shock has a significant effect (positive) on money. The GIRFs for the early reform period reveals correlations of income with inflation and nominal interest rates, but only a shock to nominal interest rates has a significant effect (positive in the early quarters) on income. The GIRFs for the later reform period reveals correlations of income with every other variable in the system excluding that a shock to real money does not have a significant effect on income. Obviously, more significant interactions between variables are revealed in the later reform period. A variance decomposition was conducted, but this requires an ordering of the variables and the results can be sensitive to the ordering, so we do not report this.

Summary of the VAR analysis. The results of the various procedures (VAR estimates, Granger causality tests, residual correlation matrix, and GIRFs) are not necessarily consistent with each other because they are capturing different aspects of the relationships between the variables. For instance, there is no Granger causality in either direction between money and income, but the GIRFs show that money shocks affect income significantly in the later reform period. For the early reform period, various procedures show that income and inflation influences money, and money influences income, inflation and exports; for the later reform period, exports and interest rates influences money, and money influences every other variable. For the early reform period, various procedures show there are two-way interactions of income with inflation and interest rates. For the later reform period, there are two-way interactions of income with exports, inflation and interest rates; money affects income, but income does not affect money. The VAR provides a statistical model of the interactions

and indicates that the later period shows more significant interactions between the variables, confirming the presence of a structural break. To go from an statistical to an economic explanation we now turn to the VECM.

4.6 Cointegration analysis

The cointegration properties of the data are investigated using the Johansen procedure. The Johansen test results are ambiguous (see Table 4.6). The trace and maximal eigenvalue cointegration tests indicates the existence of either 2 or 3 cointegrating vectors for the early reform period, and either 1 or 2 cointegrating vectors for the later reform period, depending on the assumptions about the intercept and trend.

Table 4.6 Johansen test for cointegration: Selected (5% significance level*) number of cointegrating relations by model.

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
1980Q1-1992Q4:					
Trace	3	2	2	3	3
Max-Eig	2	2	2	2	2
1993Q1-2018Q3:					
Trace	2	2	2	1	1
Max-Eig	1	2	2	2	2

Note: The Johansen test are based on the 5-variable (lm, ly, lx, PI, R) VECM4 models which do not include seasonals.

Since the Johansen test results are ambiguous, we experimented with one, two, and three cointegrating vectors to identify β and find the right cointegrating relations, $Z_t = \beta x_t$. We find that it is difficult to identify and interpret the estimation results with one or three cointegrating vectors and to get sensible conintegrating equations. So, we proceed with two cointegrating vectors for each reform period. The theory also suggests two cointegrating vectors: a long run demand for money and an IS equation. With two cointegrating vectors, we need two restrictions on each cointegrating vector to identify them. The two restrictions for the early reform period are: in the money equation, we set the coefficient of exports equal to zero, since the usual money demand theory does not mention exports and assume that the effect of exports on money works through GDP; in the second income equation, we set the coefficient of money equal to zero, assuming that money is neutral in the long run. We considered

real interest restrictions, which assumes the sum of coefficients of inflation, PI, and interest rates, R, is zero. The real interest rate restriction is rejected at 5% significance level but not at 1% level in the early reform period, and it is accepted in the later reform period by LR test for binding restrictions. These tests are reported as LR test of binding over identifying restrictions in the tables of VECM estimates below. They are Chi-square (2) since there are two restrictions, one on the real interest rate in each cointegrating vector. The results using deposit rate are given in the Appendix C, where the real interest rate restriction is also not rejected in the later period.

We finally find the following normalised money cointegrating equations for the early reform period (see Table 4.7):

$$lm_t^* = \underset{(0.078)}{1.51}\, ly_t - \underset{(0.011)}{0.04}\,(R_t - PI_t) - 2.86, \tag{4.6.1}$$

and for the later reform period (see Table 4.8):

$$lm_t^* = \underset{(0.011)}{1.46}\, ly_t + \underset{(0.002)}{0.01}\,(R_t - PI_t) - 2.42, \tag{4.6.2}$$

where lm^* is the equilibrium level of real money; the difference between interest rates and inflation, $R_t - PI_t$, is real interest rates, r_t; and the numbers in the brackets are standard errors. Throughout this paper, the numbers in brackets are standard errors.

There is no direct connection between exports and money in the long run. In both cointegrating equations (4.6.1) and (4.6.2), the scale variable, income have positive impacts on money, which is consistent with previous studies. This can be explained by the money demand theory: If the transaction scale carried out in the economy, which is measured by income, increases, then the demand for money balances will increase. In China, with other things being equal, 1% uptun of the income leads the increase of the money by 1.51% in the early reform period and 1.46% in the later reform period. The long run income elasticity of money is statistically different from one in both periods. The role of opportunity costs, real interest rate, in money demand has been significant in both periods. Its impact is negative in the early reform period, but positive and weak in the later reform period. This suggests that saving is relatively independent of the real interest rates in the later reform period. It is not clear why they have opposite signs of real interest rates in different reform periods.

We also find the following normalised income cointegrating equations for the early reform period (see Table 4.7):

$$ly_t^* = \underset{(0.027)}{0.7}\, lx_t + \underset{(0.006)}{0.01}\,(R_t - PI_t) + 3.8, \tag{4.6.3}$$

and for the later reform period (see Table 4.8):

$$ly_t^* = \underset{(0.023)}{0.68}\, lx_t - \underset{(0.006)}{0.03}\,(R_t - PI_t) + 3.94, \tag{4.6.4}$$

where ly^* is the equilibrium level of real money. The both income equations demonstrate that China is currently indeed an export driven growth Real interest rates also influence China's economy. In the later reform period, the interest rate has a negative impact on the real income, which is consistent with the theory: increasing interest rate leads that investment fall, which is a component of income.

Though the importance of different explanatory on money and income is not the same as in market economies, standard money and income functions, an IS-LM framework, can be reliably estimated for China. Tables C.2 and C.3 in the appendix show the estimates using deposit interest rates, which are similar with the estimates using lending interest rates.

4.7 Identifying the short run structure

On the basis of money cointegrating equations (4.6.1) and (4.6.2), where lm^* is the long-run demand for real money and long-run equilibrium level of real money, we investigate how variables adjust from disequilibrium to equilibrium state. The money demand function is an equilibrium condition and to make it hold all the variables can adjust. If income is too high for the money available, income may come down. In the VECM the feedback should be negative to be stabilising: if a variable is above its equilibrium value it should move down, if a variable is below its equilibrium value it should move up. This can be achieved if the long run coefficient is negative and the adjustment coefficient (error correction terms) positive, or if the long run coefficient is positive and the adjustment coefficient is negative. For example, in the early reform period, the long run coefficient on money is -1, the adjustment coefficient is negative, -0.419, and the product is positive, so the feedback is not stabilising. The long-run coefficient of income is positive, 1.51, its adjustment coefficient is negative, -0.17, and the product is negative, so the feedback is stabilising.

In the early reform stage, income and nominal interest rates' adjustment to the previous disequilibrium of money is significantly stabilising; neither money nor inflation's adjustment is stabilising. In the later reform stage, money itself (but no significance), income and nominal interest rates' adjustment to the previous disequilibrium of money is stabilising; inflation's adjustment is not stabilising. The system (money itself) corrects its previous disequilibrium by 5.7% within one quarter, but this feedback has not any statistical significance.

Table 4.7 VECM estimates for the early reform period.

Cointegrating Equation:

	lm(-1)	ly(-1)	lx(-1)	PI(-1)	R(-1)	C
CointEq1	-1	1.507	0	0.036	-0.036	-2.856
		(0.079)		(0.011)	(0.011)	
CointEq2	0	-1	0.701	-0.007	0.007	3.800
			(0.027)	(0.006)	(0.006)	

Error Correction:

	$D(lm)$	$D(ly)$	$D(lx)$	$D(PI)$	$D(R)$
CointEq1	-0.419	-0.172	-0.648	26.967	4.832
	(0.158)	(0.067)	(0.231)	(5.514)	(1.627)
CointEq2	-0.805	-0.206	-1.209	51.325	6.672
	(0.281)	(0.119)	(0.412)	(9.814)	(2.897)
R-squared	0.798	0.996	0.921	0.873	0.731
S.E. equation	0.039	0.016	0.057	1.351	0.399
Akaike AIC	-3.364	-5.074	-2.595	3.746	1.305
Schwarz SC	-2.458	-4.168	-1.690	4.651	2.211
S.D. dependent	0.062	0.199	0.146	2.734	0.555

Note 1: Standard errors are in the parenthesis. 47 observations are included. AIC is -7.146 and BIC is -2.225. Restrictions identify all cointegrating vectors at 1% significance level. The LR test for binding restrictions (rank = 2): Chi-square(2) is 7.707, and Probability is 0.021.
Note 2: In Table 4.7, the R-squared for the income growth equation is very high, 0.996, but this is a misleading indication of the degree of fit. R-squared is $1 - \frac{\sigma_u}{\sigma_y}$, where σ_u is the error variance; and σ_y is the variance of the dependent variable. Although it looks high, this is because of the variance in the dependent variable, growth. The error variance is quite large. The standard error of regression is 1.6% a quarter compared to a mean growth rate of 3.1% a quarter. But the standard deviation of the growth rate is massive, 19.9% a quarter, so the ratio of the error variance to the variance of the dependent variable is very small.

We find that in the early reform stage, exports and inflation's adjustment to the previous disequilibrium of income is significantly stabilising; neither income itself nor nominal interest rate' adjustment is stabilising. In the later reform stage, income itself, exports (but no significance) and inflation' adjustment to the previous disequilibrium of income is significantly stabilising; nominal interest rate's adjustment is not stabilising.

Furthermore, the stability of the VECM system is confirmed by the inverse roots of characteristic polynomial. With five I(1) variables, there are 2 cointegrating vectors, and 3 stochastic trends. Figure 4.5 shows the disequilibrium for the money and income cointegrating relations in the early reform stage. During the high inflation period, there was a large positive disequilibrium for money and a large negative disequilibrium for income. Figure 4.6

Table 4.8 VECM estimates for the later reform period.

Cointegrating Equation

Cointegrating Eq:						
	lm(-1)	ly(-1)	lx(-1)	PI(-1)	R(-1)	C
CointEq1	-1	1.460	0	-0.007	0.007	-2.420
		(0.011)		(0.002)	(0.002)	
CointEq2	0	-1	0.683	0.033	-0.033	3.941
			(0.023)	(0.006)	(0.006)	

Error Correction:

	$D(lm)$	$D(ly)$	$D(lx)$	$D(PI)$	$D(R)$
CointEq1	0.057	-0.071	-0.433	-13.400	-4.527
	(0.081)	(0.028)	(0.246)	(3.522)	(1.246)
CointEq2	-0.014	0.022	-0.021	-3.917	-0.167
	(0.023)	(0.008)	(0.068)	(0.978)	(0.346)
R-squared	0.394	0.998	0.795	0.690	0.471
S.E. equation	0.021	0.007	0.065	0.927	0.328
Akaike AIC	-4.656	-6.816	-2.441	2.881	0.802
Schwarz SC	-4.068	-6.228	-1.852	3.469	1.391
S.D. dependent	0.024	0.157	0.127	1.475	0.399

Note: Standard errors are in the parenthesis. 103 observations are included. AIC is -10.390 and BIC is -7.192. Restrictions identify all cointegrating vectors. The LR test for binding restrictions (rank = 2): Chi-square(2) is 1.092, and Probability is 0.579.

shows the cointegrating relations for the later reform stage. The money disequilibrium shows strong negative serial correlation and it is not clear what the reason for this. The income disequilibrium seems to be increasing in the end of the period. But both disequilibrium terms are broadly stable in each reform period.

4.8 Conclusion

This chapter uses VAR / VECM framework to estimate macroeconomic models of the Chinese economy to analyse the links between money and income, exports, inflation and interest rates. We focus on China's reform period after 1978, and a structural break in 1992 was found when China started a series of big economic reforms. So the models are estimated on two periods, the early reform period (1980Q1-1992Q4) and the later reform period (1993Q1-2018Q3).

The reduced-form VAR analysis provides a statistical model of the interactions and indicates that the later reform period shows more significant interactions between the variables,

Fig. 4.5 Cointegration graph for the early reform period.

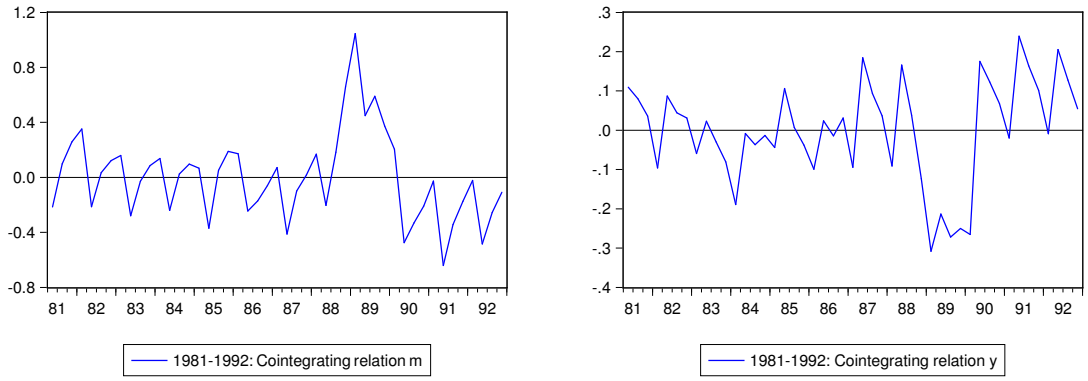
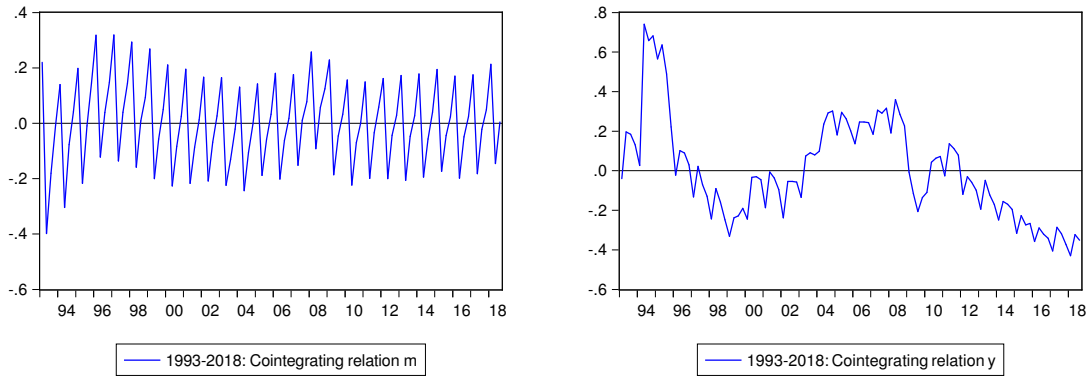


Fig. 4.6 Cointegration graph for the later reform period.



which might imply a more market-oriented economy in a later reform stage. To go from an statistical to an economic explanation, our VECM analysis suggested two cointegrating vectors between the variables considered, driven by broad money and aggregate income, resembling an IS/LM type relationship between money demand and the real economy for each reform period. The cointegrating vectors can be interpreted as (1) a long-run, money demand function in which the estimated long-run real income and real interest elasticity are respectively 1.51 (1.46) and -0.04 (0.01) over the period 1980Q1-1992Q4 (1993Q1-2018Q3) and (2) a long-run IS type income equation in which the estimated long-run real exports and real interest elasticity are respectively 0.7 (0.68) and 0.01 (-0.03) over the period 1980Q1-1992Q4 (1993Q1-2018Q3).

The impact of real interest rates on money in the early reform period and on income in the later reform peiod are reasonable: increasing opportunity cost measured by real interest

rates decreases people's speculative demand for money; and increasing interest rates leads a lower investment, which is a composition of income. It is not clear why they have opposite signs of real interest rates in two reform periods. But its positive impacts on money and income are weak, which suggests that money is relatively independent of the real interest rates in the later reform period and income is relatively independent in the early reform period. Though the importance of different explanatory on money and income is not the same as in market economies, standard money and income functions, an IS-LM framework, can be reliably estimated for China. Both disequilibrium variables, the IS-LM framework, are broadly stable. This perhaps represent a move to a more market economy. The short-run adjustment analysis shows that the PBoC can adjust interest rates (Taylor rule) or adjust money supply (McCallum rule).

These results provide important evidence on China's economic transition to a market-based system, based on stable money and goods market equilibria. A number of suggestions for future research emerge from this study. One is could we explain, if possible, theoretically, that the different elasticity of real interest rates in the long run money and income equations? Another one is to explore SVAR and monetary policy shocks, though these restrictions are not testable and economists tend not to agree on what constitute plausible restrictions.

Appendix C

Macroeconomic Interactions with money in China

Table C.1 Description of main variables, time series of quarterly data.

Abbr.	Indicator	Source
M	Banking Survey: Money Plus Quasi Money (Current billion Chinese yuan)	CEIC:1978Q1-2018Q1; NBSC: M2,2018Q2-18Q4
Y	GDP (Current billion Chinese yuan)	DS (CHXGDP..A)
y	Real GDP (2010 price)	DS (CHXGDPR.C): 1980Q1-2018Q3; DS (CHXGDPR.C): 2018Q4-19Q1
X	Exports: fob: RMB (Current billion Chinese yuan)	CEIC: 1981Q1-2018Q1; DS: 1980Q1-2018Q3
CPI	Consumer Price Index (2010Q1=100, seasonally adjusted)	Mohaddes and Raissi (2018): 1979Q2-2016Q4; CEIC: 2017Q1-18Q1; DS: 2018Q1-18Q3
PI	Quarterly Inflation in Percent Annual Rates (% pa, seasonally adjusted)	Mohaddes and Raissi (2018): 1979Q2-2016Q4; CEIC: 2017Q1-18Q1; DS: 2018Q1-18Q3
R	Lending Rate (1 year) (% pa)	CEIC: 1980Q1-2018Q1; DS (CHLDI1Y): 2018Q2-2019Q1
r	Real Lending Rate (1 year) (% pa)	CEIC: 1980Q1-2018Q1; DS (CHLDI1Y): 2018Q2-2018Q3
lm	natural logarithm of real M, m	
ly	natural logarithm of y	
lx	natural logarithm of real exports	

Note: This chapter uses data from 1980Q1-2018Q3. M approximatly equals a broad money, M2. Checking the CEIC data, we find that broad money (M2) approximatly equals narrow money (M1) plus quasi money. We could find data of "money (narrow money) plus quasi money" from 1978Q1-2018Q1 in the CEIC database, and we use it as the broad money. Broad money is the most inclusive method of calculating a given country's money supply. The money supply is the totality of assets that households and businesses can use to make payments or to hold as short-term investments such as currency, funds in bank accounts and anything of value resembling money. % pa means percent annual rates. We convert R into real interest rate, r: r (%)=[R (%) /100 - PI (%) /100)]/[1+ PI (%) /100)]*100.

Table C.2 VECM estimates for the early reform period, deposit interest rates.

Cointegrating Equation:

	lm(-1)	*ly*(-1)	*lx*(-1)	*PI*(-1)	*DR*(-1)	*C*
CointEq1	-1	1.671	0	0.021	-0.021	-4.030
		(0.011)		(0.002)	(0.002)	
CointEq2	0	-1	0.653	0.004	-0.004	4.031
			(0.022)	(0.006)	(0.006)	

Error Correction:

	D(*lm*)	*D*(*ly*)	*D*(*lx*)	*D*(*PI*)	*D*(*DR*)
CointEq1	-0.160	-0.222	-0.503	16.640	6.997
	(0.177)	(0.063)	(0.269)	(6.929)	(1.633)
CointEq2	-0.570	-0.212	-1.063	35.298	5.775
	(0.227)	(0.081)	(0.344)	(8.852)	(2.086)
R-squared	0.800	0.998	0.916	0.843	0.806
S.E. equation	0.038	0.014	0.058	1.501	0.354
Akaike AIC	-3.373	-5.430	-2.540	3.956	1.066
Schwarz SC	-2.467	-4.525	-1.634	4.862	1.972
S.D. dependent	0.062	0.199	0.146	2.734	0.581

Note: *DR* represents nominal deposit interest rates. We assume that there are 2 cointegrating vectors. Standard errors are in parentheses. 47 observations are included. AIC is -7.191 and BIC is -2.27. Restrictions identify all cointegrating vectors. LR test for binding restrictions (rank = 2): Chi-square(2) is 13.729, and Probability is 0.001.

Table C.3 VECM estimates for the later reform period, deposit interest rates.

Cointegrating Equation:

	lm(-1)	*ly*(-1)	*lx*(-1)	*PI*(-1)	*DR*(-1)	*C*
CointEq1	-1	1.464	0	-0.010	0.010	-2.435
		(0.010)		(0.002)	(0.002)	
CointEq2	0	-1	0.664	0.046	-0.046	3.980
			(0.025)	(0.008)	(0.008)	

Error Correction:

	D(*lm*)	*D*(*ly*)	*D*(*lx*)	*D*(*PI*)	*D*(*DR*)
CointEq1	0.080	-0.074	-0.658	-11.563	-5.750
	(0.084)	(0.029)	(0.253)	(3.496)	(1.490)
CointEq2	-0.006	0.016	-0.055	-3.851	-0.410
	(0.021)	(0.007)	(0.062)	(0.861)	(0.367)
R-squared	0.358	0.998	0.785	0.696	0.498
S.E. equation	0.022	0.007	0.066	0.917	0.391
Akaike AIC	-4.599	-6.755	-2.390	2.859	1.154
Schwarz SC	-4.011	-6.166	-1.802	3.448	1.742
S.D. dependent	0.024	0.157	0.127	1.475	0.489

Note: We assume that there are 2 cointegrating vectors. Standard errors are in parentheses. 47 observations are included. AIC is -9.938 and BIC is -6.74. Restrictions identify all cointegrating vectors. LR test for binding restrictions (rank = 2): Chi-square(2) is 1.07, and Probability is 0.586.

Chapter 5

Conclusion

The rapid credit expansion in China raises questions about the sustainability of China's financial development. Our knowledge about China's credit cycles and how they interact with policies, political events, and market forces, including bank-specific characteristics and macroeconomic factors, is rather limited. This is partly because most studies suppose that it is the state rather the market that largely determines China's credit cycles. This thesis tries to disentangle the role of state and market in Chinese credit booms, bank loan growth and money demand. Most studies rely on samples of groups of countries rather a single country. Although China is included in some studies, results are not directly transferable. The existence of institutional and economic disparities should not be neglected. The aim of this thesis is to contribute to a better understanding of the development of China's credit markets, their features and drivers. In particular we examine the extent to which features of the Chinese credit markets can, at least partly, be explained by economic variables, in a way that resembles features of a market economy, rather than merely being explained by state influence. Detailed findings of this study are discussed in the conclusion section of each chapter and can be summarized as follows.

Chapter 2 analyses China's credit cycles since 1978 using variables: domestic credit, claims on private sector, and broad money. Money and credit move together very closely. Chapter 2 firstly uses a band-filter to isolate cycle fluctuations in credit data. Then it provides a credit boom threshold, the standard deviation from the mean of credit cycles (and growth), and a limited threshold, its mean, by which most of Chinese credit booms can be identified. The threshold method has been applied in the literature, but we introduce a new set of threshold values that identify Chinese credit booms. Most of China's credit booms tend to spend more time to cool, which may be partly explained by the idea of a soft landing of its economy. Both, cycle and growth of credit and money variables show clustered boom peaks in 1986/1987, 1993 and 2009. The boom duration was between 1984-88, 1992-94, and

2009-11, respectively. Many booms coincided with or happened around big political and economic events, such as the 3rd Plenary Session of the 12th Communist Party of China Central Committee in October 1984, which is widely seen as paving the way towards China's transition to a market economy, and the Two Sessions in 2008, which followed the great financial crisis. Most credit booms peaked around a big Communist Party Conference or the Two Sessions, which might suggest that Chinese credit cycles are partly state-driven. Credit tended to go up before the Two Sessions and go down after. This may partly be explained by incentives of officials' promotion in conferences. In addition, we find that loose policies tend to increase credit. Policy responds negatively to past credit cycles: monetary policies are loose and window guidance encourages credit growth after credit going down. Correlations in the same period give more mixed evidence. Using several policy measures in regressions on filtered credit cycles and growth, exposes policy effects on credit cycles as largely insignificance, whilst there are some significant (and large) effects of policy on credit growth. These findings give a more nuanced picture of links between credit and policy in China.

Chapter 3 investigates the determinants of bank lending in China in a post-crisis environment, 2008-2018. We conduct a heterogeneous panel analysis of a panel of 14 Chinese listed banks, for which there is data over the period 2008Q1-2018Q4. These 14 banks represent a large share of China's banking financial system. We group these 14 banks into various bank-clusters, classified by Chinese government categories and global systemic importance. We divide the possible determinants of loan growth into two sets of variables. The first set, we label *bureaucratic variables*. These include deterministic elements like trends, seasonal effects and dummies representing state directives during the crisis plus a lagged dependent variable reflecting inertia or slow adjustment. The second set we label *economic variables*. These include bank-specific economic factors that in a market system one would expect to influence loan growth. We find that for individual banks and bank groups, bureaucratic variables are highly significant and economic variables have comparatively little influence, which is consistent with the state retraining quite a lot of control. However, pooling of the data, which constrain the coefficients to be the same across banks within a group to obtain more efficient estimates, gives more evidence for the influence of economic variables. The size of the coefficients is similar to the average of the individual banks but they are now significant, reflecting the larger sample size. Thus the pooled estimates are somewhat more supportive of the role of bank-specific market forces in determining loan growth. However, the bureaucratic variables remain important.

Chapter 4 adopts a macroeconomic perspective looking at determinants of credit growth in China. Here we investigate credit growth using broad money, given its close relationship

with credit. We use quarterly data from 1980 to 2018, which covers a longer timespan than most comparable studies. Furthermore, a long timespan allows to identify a structural break in 1992, the starting point of Deng Xiaoping's reforms and therefore a pivotal part of China's economic transformation. Various procedures are used including: an unrestricted VAR analysis and a structural vector error correction model (VECM) analysis. Our model suggests two cointegrating vectors between the variables considered, driven by broad money and aggregate income, resembling an IS/LM type relationship between money demand and the real economy. We identify a long run money demand function and an export driven long run IS relationship over 1980-2018 from a conintegrating VAR allowing for regime shifts in 1992. These results are different from previous findings, which typically only reveal one long run relationship. In addition, we find short-run adjustments which can be interpreted in terms of Taylor rule and Phillips curve relationships. These results provide important evidence on China's economic transition to a market-based system, based on stable money and goods market equilibria.

This thesis contributes to literature analysing credit cycles and booms, particularly in China's case, and our results provide important insights. A comprehensive study on the basic empirical linkages between credit and policies, political events, microeconomic and macroeconomic factors has been established. It shows there are indeed associations between movements in credit and money and institutional factors and market mechanisms. This partly reflects the progress of market-oriented economic reform including financial freedom reform. Our regression analysis provides a quantification of the relevance of credit cycles with various institutional and market factors. Overall, this thesis sheds light on the role of both the state and market playing in China's credit cycles. Its stylized facts and regression results can help guide future theoretical studies in analysing China's credit cycles, particularly their drivers.

There are of course limitations to our study. A major problem is the quality of the data and possible measurement errors. There has been concern among many commentators about the accuracy of Chinese statistics and the extent to which they are subject to political manipulation. This is a general concern throughout the thesis. But there is little that we can do about this. This thesis focuses more on the determinants of credit cycles, and less on the consequences.

In Chapter 2 we summarize the episode-by-episode development of the PBoC's monetary policy before 2001 relying on the reading of fragmented material including comments, newspapers, and papers etc. Maybe some of these materials have bias or mistakes. The People's Bank of China started to publish the electronic version of the main body of the Quarterly Monetary Policy Report to the public on a quarterly basis from the first quarter of 2001. So, we rely on the reading of these reports to construct the monetary policy

indicator from 2001 onwards. Whether it is fragmented material or reports, we have some our judgments to construct indicators. Judgments may have bias and they are not reliable as hard criteria or quantitative criteria. The monetary policy indicator is not totally consistent with the window guidance indicator. So more general questions relate to policy measurement and theoretical implications of our research, such as: Is there any better indicator to measure monetary policy; is there any further interpretation for the links between credit cycles and political events; and could we theorize the interactions or mechanisms between credit cycles and policies and political factors? need to be explored further.

In Chapter 3, our results suggest that, there remains a large degree of state influence on Chinese banks. But we do not have a clear reference point about the degree of state influence. Further promising research could attempt to compare the results on Chinese bank loan growth with that for US banks, to compare the degree to which state and market factors affected bank lending in a developed market economy post 2008. In Chapter 4, for the ones we experimented, model results seem to be robust, but may potentially be quite sensitive to specifications. The results change when we change the variables included in the VAR and the lag length used. Some of the correlations between the variables are not very strong. Thus, although we got what seem to be a well-defined money demand function, the results may be fragile. We also might need more evidence about the structural break in 1992. In future research, it will be interesting to explore the stability of money demand by applying the Markov switching VAR. In addition, we need further interpretations on why the effects of interest rates on money and income switch signs between the early and later reform periods.

There are a number of areas that may also repay further investigation. There are many more interesting questions about the role of state and market, particularly from a point of financial market development. Although China has gradually reformed its economy and financial system since 1979 to transform it to a market-based economy, there are arguments about whether China is a market economy. By May 2016, 81 countries have recognized China as a market economy. But the United States, the European Union, and Japan will again reject the economic status of the Chinese market in 2017. Our results indicate the influence of both state and market factors on Chinese credit growth. It would be also interesting to try to distinguish a good boom from a bad boom and determine the optimal policy response to credit booms, such as what the optimal policy tools are; and what the optimal political response or national regulations to credit booms are. These are interesting related topics that were beyond the scope of this thesis, but could be explored in the future.

The further research may help give a better understanding of the role that both the state and market play in the financial markets. Because there are still many questions, the findings

in this thesis can only inform, rather than dictate, supervisors' judgmental decisions regarding the appropriate policies, which will also reflect political considerations.

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